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Job and Wage Mobility in a Search Model With Non-Compliance (Exemptions) With The Minimum Wage

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Job and wage mobility with minimum wages and imperfect compliance*

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Abstract

We use a simple job search model to explain the doubling of mean hourly earnings of white males, and the five-fold increase in their variance, during the first 18 years of labor market experience. For this purpose we embody minimum wage regulations and imperfect compliance in a job search model encompassing job mobility and on-the-job wage growth as potential sources of wage dynamics. The model is estimated by simulated GMM using data from the NLSY79. Our estimated model provides a good fit for the observed levels and trends of the main job and wage mobility data, and in particular it replicates very well the increase in the first and second moments of the wage distribution over the life cycle, as well as the fall in the fraction of workers paid below the minimum wage. Our estimates imply that job mobility explains between one third and one half of the observed wage growth. Counterfactual experiments of increases in the minimum wage and/or compliance deliver small effects on both the actual wage distribution and the nonemployment rate.

Keywords: job search; wage growth; minimum wages; compliance.

JEL: J42, J63, J64

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1 Introduction

Data on labor market histories give evidence of rich employment and earnings dynamics in the years following labor market entry. Most notably, according to the National Longitudinal Survey of Youths 1979, mean hourly earnings of white, male, high-school graduates double during the first eighteen years in the labor market, and the increase in their variance is five-fold, while nonemployment rates and job mobility decline. Another interesting piece of evidence is that upon labor market entry an important fraction of high school graduates are paid below the US federal minimum wage: among white males this figure is about 20% initially, then falls to 10% in the first three years in the labor market, and settles around 2-3% from year ten onwards.[1] In this paper we intend to assess the potential of a simple job search model to jointly explain the observed employment and earnings dynamics, and in particular the three main stylized facts concerning mean earnings, their variance, and the extent of noncompliance to minimum wage regulations along young males' careers.

We will embody minimum wage regulations and imperfect compliance in an otherwise standard job search model that encompasses both job mobility and on-the-job wage growth as potential sources of wage dynamics. Both employed and nonemployed workers search for jobs, and wage offers are random draws from a known, exogenous wage distribution. Wage offers reflect firm specific productivity, as in the Lucas and Prescott (1974) islands' model. There is a minimum wage in this economy, which potentially drives out of business all firms whose productivity falls below the minimum wage, but due to imperfect compliance only a fraction of these leaves the market.

The model is estimated by simulated method of moments using data from the National Longitudinal Survey of Youths 1979. The NLSY79 provides monthly work histories for a sample of 12686 young men and women who were 14-22 years old when they were first surveyed in 1979. Our sample consists of 577 white males who graduated from high school and did not attend college, and we follow their monthly work histories for about 18 years since graduation.

Our model is estimated using two separate sets of moments, namely the sequence of monthly moments of labor market states, transitions and wages; and moments computed on employment cycles, delimited by subsequent nonemployment spells. Unobserved heterogeneity is controlled for non-parametrically by allowing for two types of workers. We allow for measurement error in observed wages, which in turn implies that wage observations below the minimum wage can stem from both noncompliance and error. However, while measurement error affects the variance of the observed wage distribution without affecting job-to-job transitions, which are instead based on true wage realizations, true wages below the minimum wage affect job mobility, and this will be

[1] Despite the findings of Ashenfelter and Smith (1979), pointing at a 25-35% rate of noncompliance to minimum wage regulations in the US, most of the recent literature on labor market effects of minimum wages has typically ignored compliance issues. More recent work by Cortes (2004) studies whether immigrants are more likely to be paid less than the minimum wage than natives and, overall, she finds no systematic pattern of noncompliance between immigrants and natives. Finally, Weil (2004) uses data on apparel contractors in the Los Angeles area, and find that 54% of employers in 2000 did not comply with minimum wage laws, and that 27% of employees were paid below the minimum wage.

the basis of our identification strategy.

The two sets of moments used for identification deliver very similar sets of parameter estimates, which have plausible magnitudes and are in line with existing estimates of search model with similar ingredients (see the extensive survey by Eckstein and van den Berg, 2007). The arrival rate of job offers is higher for nonemployed than for employed workers, and these rates differ between the two types of individuals, delivering a decreasing hazard of leaving nonemployment. With an estimated annual rate of wage growth on-the-job around 2.2-2.7%, our estimates predict that job search and mobility explain between one third and one half of total wage growth during the first 18 years of labor market experience. The rest is accounted for wage growth on-the-job.

We find that there are two (unobserved) types of workers of about equal size. One type is less employable, with relatively low arrival rates of job offers and mean wage offer, and a reservation wage below the federal minimum wage, which implies that this type is affected by minimum wage regulations. The other type has much higher arrival rates of job offers and mean wage offer, and a reservation wage above the minimum wage, and thus is not affected by the minimum wage. The estimated noncompliance rate is of about 25%. That is, a quarter of firms whose productivity falls below the minimum wage do not leave the market and offer instead wages below the minimum. This figure in turn translates into a steady state proportion of job paying less than the minimum wage equal to roughly 11%. As the US legislation on the minimum wage caters for a limited number of exemptions to minimum wage regulations that we may not fully identify in our data, this figure may also include such exempt cases.

Our estimated model fits reasonably well both sets of moments. In particular, it does a very good job at predicting the initial eighteen years of wage growth from 8 to 16 dollars per hour, the level and the upward trend in their wage variance, and the decline in the fraction of workers paid below the minimum wage. To our knowledge, this work is the first to use a simple search model to replicate both first and second moments of the wage distribution over the life cycle, as well as the extent of noncompliance to minimum wage regulations.

The comparative statics analysis of changes in the minimum wage and/or in the extent of compliance delivers limited effects of either variable on the nonemployment rate, while significantly affecting the proportion of workers paid less than the minimum wage. For example, a 25% increase in the minimum wage increases nonemployment by about 0.6-1.1 percentage points, depending on labor market experience, and this is a sort of upper bound for the employment effects of minimum wages, as (complying) firms whose productivity falls below the minimum wage have no option but to leave the market.[2]

The literature on labor market effects of minimum wage regulations is very large and we do not attempt to cover it all here.[3] However, it is well recognized that the analysis of minimum

[2]If firms had instead monopsony power and may offer wages below productivity, the minimum wage impact on nonemployment would be even smaller.

[3]Meyer and Wise (1983a, 1983b) were the first to estimate the impact of minimum wages using individual-level data. In their framework the imposition of a minimum wage leaves out of work a fraction of workers previously

wage policies requires an equilibrium model where firms and workers respond to changes in policy. Indeed a number of papers in the related literature analyze minimum wage policies in estimable search equilibrium models. In Eckstein and Wolpin (1990), who extend and estimate the equilibrium search model of Albrecht and Axell (1984), a binding minimum wage drives less profitable firms out of business, and thus shifts the wage distribution to the right and reduces the effective arrival rate of job offers to unemployed workers. van den Berg and Ridder (1998) introduce minimum wages in an equilibrium wage posting model with employed job search à la Burdett and Mortensen (1998), and obtain a continuous equilibrium wage distribution, truncated at the minimum wage. A similar equilibrium model is later used by van den Berg (2003) to study the potential of minimum wages to rule out a Pareto dominated equilibrium in an environment with multiple equilibria. Finally, Flinn (2006) estimates a matching model with Nash wage bargaining, where both the contact rate between workers and firms and the acceptance rate respond to the imposition of a minimum wage.

Similarly as in these papers, we let the wage offer distribution and the arrival rate of job offers respond to the introduction of a legally binding minimum wage. However, we adopt a simple framework with exogenous compliance to minimum wage regulations (in the spirit of Lucas and Prescott, 1974). Endogenizing firms' compliance strategies would ideally require longitudinal, linked employer-employee data. When using worker level data, as we do in this paper, this task would require strong identifying assumptions on firm behavior, which are probably not superior to our assumption of exogenous compliance, while making estimated model much less tractable.

The rest of the paper is organized as follows. Section 2 presents our job search model. Section 3 describes the data set used. Section 4 gives details of the estimation method. Section 5 presents our estimation and simulation results. Section 6 finally concludes.

2 The Search Model

We construct a continuous time search model in a stationary labor market environment with the following ingredients: (i) search on the job; (ii) minimum wages with imperfect compliance by firms; (iii) exogenous wage growth on-the-job.

We consider an economy populated by infinitely lived workers, whose mass is normalized to 1. At each moment in time a worker can be either nonemployed (a state denoted by n) or employed (a state denoted by e). When nonemployed, they enjoy some real return b (typically including the value of leisure and unemployment insurance benefits, net of search effort costs), and receive job offers at a Poisson rate λ_n. When employed, they enjoy a real wage w, which is growing at an exogenous rate g, and receive job offers at a Poisson rate λ_e.[4] Existing jobs are hit by idiosyncratic

paid below the minimum wage, and thus reduces employment. However, this result is no longer granted if firms have some degree of monopsony power (see Dickens, Machin and Manning, 1998). See also the extensive empirical evidence surveyed and provided by Card and Krueger (1995), who find no evidence of negative employment effects of minimum wages.

[4] We do not explicitly model job search behavior, and this leaves the arrival rates of job offers exogenous. Endogenizing search effort and the associated arrival rates (as we had in a previous version of this paper) would not alter

shocks, which occur at a Poisson rate δ. The instantaneous discount rate is r. New wage offers for the employed and the nonemployed are randomly drawn from some known, fixed distribution $F(w)$. Once an individual accepts a wage w, his wage on the same job grows with tenure, τ, such that $w_\tau = we^{g\tau}$.

Our wage offer distribution is motivated by underlying productivity differences across firms. This modelling choice closely resembles Lucas and Prescott (1974) islands' model, where wage dispersion stems from productivity differentials across different islands. As productivity in each island is subject to idiosyncratic shocks, workers need to spend some effort in order to locate better matching opportunities and eventually relocate across islands in pursuit of wage gains. In our model, each firm's productivity is given, but better matching opportunities arise to workers through search on-the-job.

There is an exogenously set federal minimum wage in the economy, denoted by w_M. However, compliance of firms to the minimum wage is imperfect. We normalize the number of existing firms to 1, and assume that they make zero profits. A minimum wage w_M would drive $F(w_M)$ firms out of business if they are forced to comply with minimum wage regulations, as their productivity falls short of the minimum wage. Under imperfect compliance (and possibly a small number of exemptions), only a proportion $1-\alpha$ of these firms leave the market, and workers still face some positive probability to receive a wage offer below the minimum wage. The number of operating firms is reduced to $1-(1-\alpha)F(w_M)$. As the number of firms has fallen, arrival rates of job offers both off- and on- the job needs to be adjusted accordingly. Following the matching function literature, we assume that the arrival rate is increasing and concave in the number of firms, with constant elasticity η, $0<\eta<1$.[5] Thus, the new arrival rates are $\widetilde{\lambda}_n(\alpha, w_M) = \lambda_n(1-(1-\alpha)F(w_M))^\eta$ and $\widetilde{\lambda}_e(\alpha, w_M) = \lambda_e(1-(1-\alpha)F(w_M))^\eta$. The resulting wage offer density is $\widetilde{f}(w;\alpha,w_M) = \frac{f(w)}{1-(1-\alpha)F(w_M)}$ for all $w \geq w_M$ and $\alpha\widetilde{f}(w;\alpha,w_M)$ for all $w < w_M$. The limiting case $\alpha = 0$ represents full compliance, with zero wage density for all $w < w_M$ and $\frac{f(w)}{1-F(W_M)}$ for all $w \geq w_M$. When $\alpha = 1$ there is no effective minimum wage regulation in the economy and the wage density is simply $f(w)$.[6]

Search strategies of individuals can be characterized using standard lifetime value functions. The lifetime value of employment in a job paying w_τ is $V_e(w_\tau)$, where τ denotes tenure on the current job. The lifetime value of nonemployment is denoted by V_n. As $V_e(w_\tau)$ increases with w_τ while V_n is independent of w_τ, there exists a unique reservation wage w^* such that $V_n = V_e(w^*)$. The optimal search strategy of the nonemployed consists therefore in accepting the first wage offer at or above the reservation wage. By the same argument, the employed optimally accept the first wage offer at or above their current wage.

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our main results.

[5] Typically matching rates would depend on the number of firms and the number of jobseekers, but the number of jobseekers is here normalized to 1.

[6] Introducing an exogenous noncompliance parameter α is a simple way to keep the wage offer distribution continuous and differentiable. Modelling explicitly compliance decisions, while going beyond the scope of this paper, generates a spike at the minimum wage and a discontinuity in the wage distribution (see Ashenfelter and Smith, 1979 and Lott and Roberts 1995).

If $w_M \leq w^*$, minimum wages have no impact on agents' decisions or equilibrium outcomes. Therefore, we consider the case in which the minimum wage is binding , i.e. $w_M > w^*$, and the flow value of unemployment can be written as:

$$rV_n = b + \widetilde{\lambda}_n(\alpha, w_M)\left[\alpha \int_{w^*}^{w_M} [V_e(w) - V_n]\, \widetilde{f}(w;\alpha, w_M)dw + \int_{w_M} [V_e(w) - V_n]\, \widetilde{f}(w;\alpha, w_M)dw\right] \tag{1}$$

Similarly, the flow value of employment is given by:

$$\begin{aligned} rV_e(w_\tau) &= w_\tau + gw_\tau V_e'(w_\tau) + \delta\left[V_n - V_e(w_\tau)\right] \\ &+ \widetilde{\lambda}_e(\alpha, w_M)\int_{w_\tau} [V_e(w) - V_e(w_\tau)]\, \widetilde{f}(w;\alpha, w_M)dw \text{ for } w_\tau \geq w_M, \end{aligned} \tag{2}$$

$$\begin{aligned} rV_e(w_\tau) &= w_\tau + gw_\tau V_e'(w_\tau) + \delta\left[V_n - V_e(w_\tau)\right] \\ &+ \widetilde{\lambda}_e(\alpha, w_M)\left[\alpha\int_{w_\tau}^{w_M} [V_e(w) - V_e(w_\tau)]\, \widetilde{f}(w;\alpha, w_M)dw \right. \\ &\left. + \int_{w_M} [V_e(w) - V_e(w_\tau)]\, \widetilde{f}(w;\alpha, w_M)dw\right] \text{ for } w_\tau < w_M. \end{aligned} \tag{3}$$

where terms in $V_e'(w_\tau)$ represent the appreciation in the value of employment due to tenure effects.

The value of the reservation wage can be solved for by setting equation (1) equal to equation (3), evaluated at $w = w^*$ and $\tau = 0$, exploiting the continuity of $V_e(w_\tau)$ at w_M:

$$\begin{aligned} w^* &= b - gw^*V_e'(w^*) + \left(\widetilde{\lambda}_n(\alpha, w_M) - \widetilde{\lambda}_e(\alpha, w_M)\right) \\ &\quad \left[\alpha\int_{w_\tau}^{w_M} [V_e(w) - V_n]\, \widetilde{f}(w;\alpha, w_M)dw + \int_{w_M} [V_e(w) - V_n]\, \widetilde{f}(w;\alpha, w_M)dw\right] \\ &= b - gw^*V_e'(w^*) + \left(\widetilde{\lambda}_n(\alpha, w_M) - \widetilde{\lambda}_e(\alpha, w_M)\right) \\ &\quad \left[\int_{w^*} [1 - \widetilde{F}(w;\alpha, w_M)]V_e'(w)\, dw - (1-\alpha)\int_{w^*}^{w_M} [\widetilde{F}(w_M;\alpha, w_M) - \widetilde{F}(w;\alpha, w_M)]V_e'(w)\, dw\right], \end{aligned} \tag{4}$$

where $\widetilde{F}(.;\alpha, w_M) = \frac{F(.)}{1-(1-\alpha)F(w_M)}$.

To solve the model one still needs to obtain an expression for $V_e'(w_\tau)$. In Appendix A we derive the explicit solution for $V_e'(w_\tau)$ for $w_\tau \geq w_M$ (equation 13) and $w_\tau < w_M$ (equation 14). Substituting (13) and (14) into (4) gives a unique solution for the reservation wage, which enables us to fully characterize search decisions and simulate labor market dynamics. In the rest of the paper this framework will be used to simulate and estimate transitions from the first nonemployment spell after education into employment, the subsequent job-to-job mobility and associated wage growth, and transitions back into nonemployment following involuntary job loss. Based on these, we will estimate the probability of nonemployment and that of employment, distinguishing between below and above the minimum wage.

This framework is also useful to describe the impact of changes in the minimum wage on nonemployment. An increase in the minimum wage lowers the arrival rate of job offers for both the employed and the nonemployed in the same proportion. If the nonemployed have higher arrival rates than the employed, as typically the case, the absolute fall in $\widetilde{\lambda}_n(\alpha, w_M)$ is going to be greater than the absolute fall in $\widetilde{\lambda}_e(\alpha, w_M)$, and this tends to lower the reservation wage. At the same time it raises the expected value of all acceptable wage offers (first term in the bottom row of equation (4)) and removes some mass of firms paying below w_M (second term in the bottom row of equation (4)). The impact of higher minimum wages on the reservation wage is thus ambiguous. A fall in α, meaning better compliance of firms to minimum wage regulations, has the same impact of an increase in w_M : it lowers arrival rates of job offers and has an ambiguous impact on the reservation wage.

The impact of the minimum wage and compliance on nonemployment is solely determined by the unemployment exit hazard, given that the job destruction rate δ is exogenous. Such hazard is given by

$$h_n(\alpha, w_M) = \widetilde{\lambda}_n(\alpha, w_M) \left[1 - (1-\alpha)\widetilde{F}(w_M; \alpha, w_M) - \alpha \widetilde{F}(w^*; \alpha, w_M)\right].$$

While the arrival rate $\widetilde{\lambda}_n(\alpha, w_M)$ falls with w_M and $1-\alpha$, the impact of these two variables on w^* and therefore on the acceptance rate $[1 - (1-\alpha)\widetilde{F}(w_M; \alpha, w_M) - \alpha \widetilde{F}(w^*; \alpha, w_M)]$ is ambiguous. Empirically, it will turn out that the minimum wage and compliance parameters have a negligible impact on the reservation wage, and thus most of the action of minimum wage regulations on nonemployment comes through a reduction in the arrival rate of job offers.

3 Data

We use data drawn from the National Longitudinal Survey of Youths, which contains information on a sample of 12,686 respondents who were between 14 and 22 years of age in January 1979 (NLSY79). We attempt to obtain a sample from a fairly homogenous population, which is relatively likely to participate in the labor force and receive wage offers below the minimum wage. For this purpose we include in our sample white, high school graduate males. Specifically, we select non-black, non-hispanic, males who have completed at most 12 years of schooling and declare to hold a high school degree. We exclude from our sample those who (i) ever went to the army; (ii) ever declared to be in college; (iii) ever declared to have a college or professional degree. We further restrict our sample to those who completed high school between age 17 and 19. These restrictions leave us with a sample of 577 individuals, with almost 12(months)x18(years) work history observations per-individual. Individuals in our sample completed high school between 1974 and 1984. More than 95% of them graduated in either May or June.

Information on selected respondents is available since January 1978. We construct individual monthly work histories using answers to retrospective questions. We assume that market entry coincides with the month an individual completed high school.

Labor Market States From the NLSY79 work history file, we obtain individuals' monthly employment status from January 1978 to December 1998. We define an individual as employed in a given month if he works at least 10 hours per week and at least three weeks in the month, or during the last two weeks in the month. Otherwise, an individual is classified as nonemployed, and we do not further distinguish between unemployed and out of the labor force.

The employment history information is employer-based. All references to a "job" should be understood as references to an employer. Multiple jobs held contemporaneously are treated as new jobs altogether, with an associated wage equal to the average of hourly wages, and working hours equal to the sum of working hours on the different jobs. Tenure on a job is considered as completed when a new job is recorded or when an individual is back in nonemployment. Figure 1 shows the monthly proportion of employed and nonemployed by time since high school graduation. As expected, the data show a trend increase in employment rates and clear patterns of seasonality.

We find that 55% of individuals employed in the month they finished high school started work in the year before graduation. This may happen because job search starts while in school or, more likely, because high school students may take up temporary and part time jobs while in school. The latter explanation seems also supported by the clear seasonal pattern of employment rates during the last year before graduation. We assume that individuals employed before graduation enter the "official" labor market upon graduation, but we will treat the proportion of individuals employed at labor market entry as an initial condition in our analysis.

Table 1 reports the duration of nonemployment spells leading to the first 10 jobs in individual careers, which seems to fall roughly monotonically with the job rank. 131 individuals had more than 10 jobs, 12 of whom had more than 20 jobs. The maximum number of jobs held is 27. As we have several censored spells in our sample, the sample mean duration is downward biased. In columns 4 we therefore also present the Kaplan-Meier nonparametric durations estimates.[7] Average nonemployment duration is about nine months, and the correction for censoring adds one month. Job duration increases from the first to the second job, but from the third job onwards duration falls. Obviously, selection and sample attrition are important factors for these observations.

Figure 2 plots the job separation hazard by job tenure. We do not distinguish among job ranks, due to the insufficient number of observations for each rank. Duration is truncated at 10 years (and consequently 83 out of 2539 job spells are dropped). The monthly job hazard rate decreases significantly with duration, consistently with a search model with wage growth on-the-job.

Figures 3 and 4 show labor market transition rates by potential experience. All transitions display some trend during the first ten years and then they stay constant for the additional eight years. Furthermore, there is strong evidence of seasonality, with large monthly fluctuations. The probability of staying on the same job increases from 65% to 90% over 18 years of labor market

[7] Let n_t be the population alive at time t and d_t the number of failures. The nonparametric maximum likelihood estimate of the survivor function is: $\widehat{S}(t) = \Pi_{j|t_j \leqslant t}(\frac{n_j - d_j}{n_j})$. The Kaplan-Meier restricted mean duration is computed as the area under the Kaplan-Meier survivor function. And the associated standard error is given by the Greenwood formula: $\widehat{Var}\{\widehat{S}(t)\} = \widehat{S}^2(t) \sum_{j|t_j \leqslant t} \frac{d_j}{n_j(n_j - d_j)}$.

Table 1: Duration (months) of non-employment spells and job spells since high school gradaution

Job No.	No. of obs.	Sample Mean duration (s.d.)	Kaplan-Meier restricted Mean duration (s.d.)
NE*	148	8.86 (23.90)	9.93 (2.37)
1	574	32.74 (53.94)	38.69 (2.76)
2	508	33.77 (49.05)	41.03 (2.85)
3	457	27.82 (38.35)	39.37 (3.10)
4	387	24.71 (33.28)	34.06 (2.77)
5	337	22.22 (30.91)	31.23 (2.73)
6	276	20.38 (28.84)	32.33 (3.83)
7	236	23.23 (31.30)	34.59 (3.40)
8	182	17.92 (25.78)	24.82 (3.07)
9	150	17.58 (19.22)	21.51 (2.12)
10	131	16.96 (22.31)	24.19 (3.40)

experience (Figure 3). The probability of remaining out of work decreases from 20% to about 8%, and that of moving from employment to nonemployment decreases from about 5 to 2%. The probabilities of moving from nonemployment to employment and from job to job (Figure 4) fall from about 5% to less than 2% and have relatively large fluctuations. An important goal of the search model described above is to fit the levels and trends of these transition rates, although not necessarily the monthly seasonal fluctuations.

Wages and Employment Cycles We next define employment cycles, in order to set the data in a way that is consistent with our search model (see also Wolpin, 1992). Each cycle starts with nonemployment and terminates with the last job before a subsequent nonemployment spell. For individuals who start working before graduation, the first cycle starts with their first job instead of nonemployment. For an individual i, the sequence of cycles is denoted by

$$\{c_i^1(ne_i^1, J1_i^1, J2_i^1, \cdots), c_i^2(ne_i^2, J1_i^2, J2_i^2, \cdots), \cdots\},$$

where c_i^j denotes cycle j for individual i, ne_i^j denotes nonemployment spells, and $J1_i^j, J2_i^j, ...$ denote job spells within each cycle. We also record wages in each job spell.

The NLSY collects data on respondents' usual earnings (inclusive of tips, overtime, and bonuses, before deductions) during every survey year for each employer for whom the respondent worked since the last interview date. The amount of earnings, reported in dollars and cents, is combined with information on the applicable unit of time, e.g. per day, per hour, etc. Combining earnings and time unit data, the variable "hourly rate of pay job #1-5" in the work history file provides the hourly wage rate for each job. We use coded real hourly wage in 2000 dollars. Nominal wage data are deflated using the monthly CPI from BLS. We top and bottom code the hourly wage at 150$ and 1.0$, respectively, up until 1990; and at 200$ and 1.5$ afterwards.

We will focus our analysis of earnings on real hourly wages. The mean wage in the sample increases from 8$ upon high school graduation to 16$ after eighteen years (see Figure 10). The standard deviation of wages also doubles during this time period, from 4$ to 8$ (see Figure 11). We also compute mean wages in subsequent jobs within employment cycles. As expected, mean wages increase with job moves within cycles. When a new cycle starts, the mean wage on the first job is lower than the mean wage on late jobs of previous cycles (see the data series in the second row of Table 5).

The minimum wage The federal minimum wage for covered nonexempt employees is currently at \$5.15 an hour. Figure 5 describes the increase in the federal minimum wage between 1978 and 2002, from \$2.65 to \$5.15. However, the real minimum wage, deflated by monthly CPI-U and expressed in 2000 dollars, has been decreasing during this sample period. Several states also have state-level minimum wage laws. Where an employee is subject to both state and federal minimum wage laws, he is entitled to the higher of the two. Seven states have no minimum wage law, namely Alabama, Arizona, Florida, Louisiana, Mississippi, South Carolina and Tennessee. Four states have minimum wage rates lower than the Federal level, namely Kansas, New Mexico, Ohio and Virgin Islands. All other states have minimum wage rates that are equal or higher than the Federal level. In our estimates we will only take into account the time path of the federal minimum wage.

Some minimum wage exemptions apply under specific circumstances. For example, a minimum wage of \$4.25 per hour applies to workers under the age of 20 during their first 90 consecutive calendar days of employment with an employer. After 90 days or when the employee reaches age 20, he or she must receive a minimum wage of \$5.15. Full-time students can be paid not less than 85% of the minimum wage before they graduate or leave school for good. Student learners aged 16 or more can be paid not less than 75% of the minium wage for as long as they are enrolled in the vocational education program. Workers normally receiving tips are also exempt from minimum wage regulations.[8] Most important exemptions should not feature in our data, as we exclude students from our sample, and although we include tipped workers, their wage data are inclusive of tips. Having said this, other exemptions would be considered as part of noncompliance with minimum wage regulations.

Looking at the data series in Figure 14, about 20% of individuals in our sample work below the federal minimum wage upon high-school graduation. This proportion falls to 10% in the first three years of labor market experience, and seems to settle around 2-3% from the tenth year onwards. Furthermore 47% of the individuals are observed to work for a wage below the minimum wage for at least one month. For these workers the average number of months worked below the minimum wage is 13.5, and the average number of jobs held below the minimum wage is 1.5. The mean job duration below the minimum wage is 8.9 months. These facts indicate that, if wages are reported

[8]Exemptions are documented by the US Department of Labor, Employment Standards Administration Wage and Hour Division at www.dol.gov/esa/

Table 2: Mean duration of nonemployment and jobs in months

	First Cycle	Second Cycle	Third Cycle
NE	7.3 (116)	5.8 (311)	5.8 (242)
To job 1 above w_M	7.2 (87)	5.3 (264)	5.0 (217)
To job 1 below w_M	7.7 (29)	8.7 (47)	12.6 (25)
Job 1	29.6 (306)	27.5 (311)	23.9 (242)
Above w_M	31.0 (239)	29.4 (264)	25.0 (217)
Below w_M	24.5 (67)	17.3 (47)	14.4 (25)
Job 2	40.3 (192)	27.5 (178)	27.8 (125)
Above w_M	42.3 (179)	27 (165)	29.8 (115)
Below w_M	12.9 (13)	34.4 (13)	5.2 (10)
Job 3	39.4 (132)	25.9 (84)	21.1 (71)
Above w_M	39.8 (130)	26.9 (77)	22.1 (67)
Below w_M	13.5 (2)	14.9 (7)	3.5 (4)
Job 4	31.2 (77)	21.5 (56)	19.6 (39)
Above w_M	31.0 (70)	21.7 (55)	18.9 (38)
Below w_M	32.7 (7)	12 (1)	45 (1)
Job 5	25.2 (42)	18.5 (29)	20.6 (24)
Above w_M	25.7 (41)	18.5 (29)	20.6 (24)
Below w_M	5 (1)	-	-

Number of observations is in parentheses. All statistics are conditional on wage being observed and this is why there is little discrepancy between moments in table 6 and 9.

without error, noncompliance with the minimum wage law is quite important among young high school graduates.

Table 2 presents the mean duration of nonemployment and of the first five jobs in the first three cycles, distinguishing between pay above and pay below the minimum wage. The mean duration from nonemployment to the first job is lower for jobs paying at least the minimum wage. Also, mean tenure on jobs paying at least the minimum wage is always longer than mean duration on jobs paying less than the minimum wage.

Table 3 gives the number of individuals making transitions from nonemployment to jobs, and between jobs, again conditional on wages above or below the minimum wage. Most transitions to jobs paying less than the minimum wage originate in nonemployment, and most workers earn wages above the minimum wage once they switch job. Very few workers are observed to move from a job paying more than the minimum wage to one paying less. Transitions from higher-paying to lower-paying jobs can only be reconciled with our model if observed wages are measured with error. In our estimates we thus attempt to separately identify measurement error in wages and noncompliance.

Table 3: Transitions to employment and from job-to-job (no. of obs.)

	First Cycle	Second Cycle	Third Cycle
Unemployed	(116)	(311)	(242)
UE to J1 above w_M	87	264	217
UE to J1 below w_M	29	47	25
First Job above w_M	(239)	(264)	(217)
Move to J2 above w_M	93	123	88
Move to J2 below w_M	4	6	6
First Job below w_M	(67)	(47)	(25)
Move to J2 above w_M	22	14	11
Move to J2 below w_M	4	2	2
Second Job above w_M	(179)	(165)	(115)
Move to J3 above w_M	86	67	50
Move to J3 below w_M	2	5	2
Second Job below w_M	(13)	(13)	(10)
Move to J3 above w_M	4	5	5
Move to J3 below w_M	0	2	1
Third Job above w_M	(130)	(77)	(67)
Move to J4 above w_M	59	48	33
Move to J4 below w_M	6	0	1
Third Job below w_M	(2)	(7)	(4)
Move to J4 above w_M	2	2	1
Move to J4 below w_M	0	0	0
Fourth Job above w_M	(70)	(55)	(38)
Move to J5 above w_M	31	28	18
Move to J5 below w_M	1	0	0
Fourth Job below w_M	(7)	(1)	(1)
Move to J5 above w_M	6	0	1
Move to J5 below w_M	0	0	0

4 Estimation

Specification. We estimate the model using simulated moments. We allow for unobserved heterogeneity in arrival rates, job destruction rates and in the parameters of the wage offer distribution by assuming that there are two types of individuals in the population, with π denoting the proportion of type one. The wage density function is assumed to be log normal, $\ln w \sim N(\mu, \sigma_w^2)$. We allow for measurement error in observed wages, such that $\ln w^o = \ln w + u$, where w^o is the observed wage, w is the true wage and the error term is log-normally distributed: $u \sim N(0, \sigma_u^2)$. The time preference parameter r is known to be 4% annually, which is 0.3% monthly. We cannot estimate the matching function parameter η directly, as in order to identify it one should need data on firms or vacancies. As in much of the related literature, we set $\eta = 0.5$ (see Petrongolo and Pissarides, 2001, for supporting evidence), but we perform some sensitivity analysis on η and will briefly comment on the results obtained for the extreme cases $\eta = 0$ and $\eta = 1$. The bottom line is that our results are not very sensitive to the chosen value for η.

As 55% of individuals in our sample worked before graduation, we assume that a separate labor market exists before graduation, and we characterize this labor market by an initial (period 0) reservation wage w_0^*.[9] We estimate the reservation wage directly using equation (9).[10] The parameters of the model to be estimated are in the vector
$\theta = [\lambda_{n1}, \lambda_{e1}, \lambda_{n2}, \lambda_{e2}, w_1^*, w_2^*, \mu_1, \mu_2, \sigma_{w1}, \sigma_{w2}, \delta_1, \delta_2, w_{01}^*, w_{02}^*, \pi, \sigma_u^2, \alpha, g]'$.

Data As described above, we have a sample of white male high school graduates indexed by $i = 1, ..., 577$. Let $d_{it_i} = 1$ if the individual is working and $d_{it_i} = 0$ if the individual is not working, where t_i is the month after graduation or, equivalently, the month since entry in the labor market. We observe $[d_{it_i}^D, w_{it_i}^D]$ for $i = 1, \cdots, 577$ and $t_i = 1, \cdots, T_i$, where the superscript D denotes the data.

Simulations. We simulate both conditional moments, i.e. predicted values of wages and employment, conditional on the observed (data) values in the previous month, and unconditional moments, which only depend on the simulated values for the previous month.

Initially at $t = 0$, we have both employed and nonemployed individuals. If an individual is employed, we simulate a wage w_{i0} such that $w_{i0} \geq w_0^*$. Starting from the first month ($t = 1$), if an individual is nonemployed, with probability λ_n he receives a random wage draw from a distribution

$$\frac{\phi(w)}{1 - (1-\alpha)\Phi(w_M)} \quad \text{for } w \geq w_M \tag{5}$$

$$\frac{\alpha\phi(w)}{1 - (1-\alpha)\Phi(w_M)} \quad \text{for } w < w_M \tag{6}$$

[9] Wolpin (1987) documents similar evidence and argues that it is consistent with the notion that the search process begins prior to graduation.

[10] Allowing for measurement error in reported wages enables us to estimate the reservation wage by the moments rather than by the lowest observed wage.

where $\phi(\cdot)$ is the log normal wage density function with mean μ and variance σ_w^2 and $\Phi(\cdot)$ is the corresponding c.d.f.. If the wage offer is above w^*, he moves from nonemployment to employment. When he is employed at wage w_{it}, with probability λ_e he receives a random wage draw from the distribution (5)-(6). If $w' > w_{it}$, he moves on to the new job. Otherwise he stays on the current job and his wage increases to $w_{it+1} = w_{it}(1+g)$. In any period he may go back to nonemployment with probability δ.

Let's first consider all individuals who have observations on $d_{it_i}^D, w_{it_i}^D$ from $t_i = 1, ...T_i$, i.e. that are not left-censored. In a *conditional* simulation s, the model predicts $d_{it_i}^s$ and $w_{it_i}^s$, conditional on $d_{it_i-1}^D$ and $w_{it_i-1}^D$. If an individual is working and a wage is observed, we simulate the measurement error to obtain the "true" wage according to $w_{it_i}^{TD} = w_{it_i}^D - u$, where TD indicates a predicted "true" wage that should be related to the observed wage. Conditional on the "true" wage in $t_i = 1$, we simulate the outcome for $t_i = 2$, i.e. $[d_{it_i=2}^s, w_{it_i=2}^s]$. We thus generate a sequence of simulated observations $[d_{it_i}^s, w_{it_i}^s]$ for $t_i = 1, ..., T_i$, that follow the true sequence $[d_{it_i-1}^D, w_{it_i-1}^{TD}]$ for $t_i = 1, ..., T_i$. When a wage is not observed, the simulated wage is dropped from the simulated sample. In an *unconditional* simulation s, the prediction of $[d_{it_i}^s, w_{it_i}^s]$ is conditional on the last period simulations $[d_{it_i-1}^s, w_{it_i-1}^s]$. For all i and t, in all specifications we run $N^S = 25$ simulations.

For the left censored observations, suppose that the first observation for individual i is available at $t_i = 2$. The simulation for period 2 is based on the sequence of two simulations: we first simulate period 1 employment status and wages, and conditional on these we simulate period 2 employment status and wages, $[d_{it_i=2}^s, w_{it_i=2}^s]$. Similarly if the first available observation is at point in time 3.

Monthly moments and identification We use two sets of moments: the first set is computed by months in the labor market, and the second set is computed by employment cycle.. Among the monthly moments, the conditional ones include the nonemployment rate mne; the proportion of individuals who move from nonemployment to employment mtr_1; the proportion of individuals who move from job to job mtr_2; the proportion of individuals who move from employment to nonemployment mtr_3; the mean wage mw_1; its standard deviation mw_2; the mean wage below the minimum wage mw_3; and the standard deviation of the wage below the minimum wage mw_4. The unconditional moments include all previous 8 moments, plus the proportion of individuals that work below the minimum wage mp. All these moments are computed from the data and simulated 25 times, either conditionally or not. The simulated moments used in estimation are the averages across all simulations (See Appendix B for the exact definitions of moments).

Transition moments from nonemployment to employment are used to identify the offer arrival rate when nonemployed. Similarly, job-to-job transitions identify the offer arrival rate when employed and transitions from employment to nonemployment identify the job destruction rate. The reservation wage is identified by the nonemployment rate. Wage moments can identify the parameters of the wage distribution. In particular, the initial wage identifies the initial reservation wage. The mean and the variance of the wage offer distribution are identified from the observed monthly mean and variance as well as from the transitions from job-to-job.

A key aspect of the paper is the identification of the noncompliance parameter α. The proportion of workers who earn below the minimum wage identifies α, but it should be noted that this moment is also affected by measurement error in observed wages. However, measurement error also affects the variance of the observed wage distribution without affecting the job-to-job transitions, and this will be the basis of our identification strategy. Conditional on the variance of the observed wage offer distribution and job-to-job transitions, the proportion of workers earning less than the minimum wage allows us to separately identify α and σ_u^2.

Cycle moments and identification The second set of moments are based on the first three employment cycles. We first use duration moments, namely mean nonemployment and employment duration on the first three jobs in the first three employment cycles. Second, we use wage moments, namely mean and standard deviation of wages (either global or below the minimum wage) on the first three jobs in the first three cycles. Third, we use transition moments, including the proportion of individuals who start the first three cycles from nonemployment, the proportion of individuals who move from the first to the second job, from the second to the third job in the first three cycles. Last, we also use the proportion of individuals who work below the minimum wage on the first three jobs in the first three cycles.

As with monthly moments, nonemployment duration identifies the offer arrival rate when nonemployed. Job-to-job transitions identify the offer arrival rate when employed. The reservation wage is identified by the wage on the first job. The mean and variance of the wage offer distribution are identified by the mean wage and its standard deviation. The job destruction rate is identified by the nonemployment rate when new cycles start. The initial reservation wage is identified by the initial nonemployment rate and the mean wage on the first job in the first cycle (being significantly lower than the wage on the first job in the second and third cycles). The proportion of individuals earning below the minimum wage and the variance of the observed wage identify α and σ_u^2, as discussed above.

Implementation. We implement the simulated method of moments (SMM) using these two sets of moments described. Let mom_j^D be moment j in the data and $mom_j^S(\theta)$ be moment j from the model simulation, given the parameter vector θ. The moment vector is

$$g(\theta)' = [mom_1^D - mom_1^S(\theta), \cdots, mom_j^D - mom_j^S(\theta), \cdots, mom_J^D - mom_J^S(\theta)]$$

where J is the total number of moments. With monthly moments, $J = 3672$ and with cycle moments, $J = 66$.[11] The objective function to be minimized with respect to θ is

$$J(\theta) = g(\theta)'Wg(\theta),$$

[11] The first set of moments include 8 series of conditional monthly moments and 9 series of unconditional monthly moments, so J=17*216=3672. The second set of moments consist of 12 duration moments, 36 wage moments, 9 transition moments and 9 moments on proportions below the minimum wage.

Table 4: Parameter estimates of a search model

Parameters	Estimates based on monthly moments		Estimates based on cycle moments	
	coef.	(s.e.)	coef.	(s.e.)
λ_{n1}	0.428	(0.091)	0.476	(0.337)
λ_{n2}	0.658	(0.368)	0.765	(0.648)
λ_{e1}	0.116	(0.125)	0.124	(0.029)
λ_{e2}	0.237	(0.098)	0.237	(0.046)
π	0.499	(0.064)	0.499	(0.066)
w_1^*	2.496	(1.416)	2.496	(4.771)
w_2^*	11.065	(1.585)	10.760	(2.272)
μ_1	1.620	(0.231)	1.619	(0.128)
μ_2	1.652	(0.185)	1.652	(0.086)
σ_{w1}	0.492	(0.162)	0.501	(0.107)
σ_{w2}	0.517	(0.082)	0.516	(0.036)
δ_1	0.063	(3.44e-3)	0.045	(0.009)
δ_2	4.13e-3	(1.37e-3)	0.012	(9.56e-4)
w_{01}^*	2.871	(0.460)	2.900	(3.869)
w_{02}^*	6.791	(0.639)	7.486	(0.459)
σ_u	0.012	(5.84e-3)	7.86e-3	(0.011)
α	0.259	(0.091)	0.279	(0.069)
g	2.27e-3	(1.45e-3)	1.85e-3	(4.09e-4)

Notes. The sample includes male high-school graduates from the NLSY. Number of observations: 577. Estimation methods: Simulated GMM.

where the weighting matrix W is set to be diagonal.[12]

5 Results

5.1 Estimates

Our main results are presented in Table 4, where the two sets of estimates are based on our two sets of moments. The two (unobserved) types of individuals are allowed to differ in all parameters but in the level of compliance α, the measurement error variance σ_u and wage growth on-the-job, g.

Starting from estimates on monthly moments, our parameter values have plausible magnitudes and are in line with previous estimates of the parameters of a search model with search on-the-job. That is, arrival rates of job offers are higher for the nonemployed than for the employed, and these rates are different across types of individuals, delivering a decreasing hazard rate. Type 1 individuals, representing almost exactly a half of our sample, have lower job offer arrival rates while both nonemployed and employed, a higher job destruction rate, a lower mean wage offer and a lower reservation wage. This is the only group whose reservation wage is below the minimum wage,

[12]In our estimates, the weight on each moment is set to be one over its sample mean for the monthly moments. We use the identity matrix as the weighting matrix for cycle moments.

and thus the only one for which minimum wage regulations matter. In other words, changes in minimum wages and/or compliance rates do not affect half the population of high school graduates. One would expect that reservation wages during the final year of high school are lower than after graduation, and this is indeed the case for type-2 individuals, while the two reservation wage values are not significantly different from each other for type-1 individuals.

The types are identified from the panel dimension of the data. One way to illustrate identification is to look at the posterior probability of being type 1, conditional on a particular event. For example, one can compute the posterior probability of being type 1, conditional on observing a transition form employment to nonemployment. Given the model estimates, this is

$$\begin{aligned}\Pr\left(type\ 1|e \rightarrow ue\right) &= \frac{\Pr\left(e \rightarrow ue|type\ 1\right)\Pr(type\ 1)}{\Pr\left(e \rightarrow ue\right)} \\ &= \frac{\delta_1\pi_1}{\delta_1\pi_1+\delta_2\pi_2} = 0.938\end{aligned}$$

implying that type-1 individuals represent about 94% of employment to nonemployment transitions.

The novelty of our results consists in providing an estimate for the extent of noncompliance of firms' wage offers to minimum wage regulations, represented by the parameter α. We find that the arrival rate of job offers below the minimum wage is about a quarter of that above the minimum wage. Having estimated α, the steady state proportion of jobs that pay less than the minimum wage is given by

$$\frac{\pi_1\alpha[F_1\left(w_M\right)-F_1\left(w_1^*\right)]}{\pi_1[1-F_1\left(w_1^*\right)]+\pi_2[1-F_2\left(w_2^*\right)]} = 0.114.$$

This number is clearly lower than α as only type 1 individuals are affected by the compliance level. Furthermore, it is only the density of offers between the reservation wage of type-1 individuals and w_M that matters for the job count below w_M.

Finally, wage growth on-the-job is 0.227% per month, corresponding to 2.75% per year. This estimate is close to the upper bound for wage growth on-the-job suggested by Bowlus and Neumann (2006) on the NLSY. One can use this estimate to infer the proportion of wage growth that is explained by job search and mobility, as opposed to wage growth on-the-job. Over the entire sample period, the mean hourly wage grows by \$8.10, from \$8.32 in the first month to \$16.42 in the last month. An individual who is spending this 18 years span on the same job would see his wage increase by \$5.23, from \$8.32 to $8.32*(1+2.27e-3)^{215} = 13.55$. Thus 64.6% of wage growth is due to on-the-job growth and the remaining 35.4% is due to job mobility. These figures are very close to those reported by Topel and Ward (1992), who find that wage gains attributable to job mobility explain about one third of total earnings growth during the first ten years of labor market experience.

The estimates obtained on cycle moments are quite similar to those obtained on monthly moments, including the ranking of values for type 1 and type 2 individuals. Two differences may be worthwhile mentioning. First, when using cycle moments we obtain a lower (and non-significant) estimate of the measurement error variance, but the estimate for α stays very similar to that obtained on monthly moments. Second, wage growth on-the-job is slightly lower, predicting a virtually equal role of job mobility and wage growth on-the-job in explaining wage growth during the first 18 years of labor market experience.

5.2 Model Fit

Figures 6-13 show the fit of all the monthly moments that are used for estimation of the parameters of interest. In general the estimates from conditional simulated moments do quite a good job at reproducing the data moments in terms of the eighteen-year trends, levels and seasonal fluctuations.

The model fits well the life cycle decrease in nonemployment (Figure 6), and the slight increase in the transition rate from nonemployment to employment (Figure 7) during the first 10 years in the labor market, but fails to fit the increase in the seasonal fluctuations in these transition rates. The model also fits well the decrease in job-to-job transitions (Figure 8): but while conditional moments also fit well its level, the unconditional ones seem to underpredict mobility. Finally, the model fails to fit the decreasing trend in transitions from employment to nonemployment, but it does fit its level (Figure 9). This failure is sort of expected, as transitions into nonemployment are driven by an exogenous job destruction rate, which would not respond to tenure, wages or seasonal factors.[13] Indeed, the only potential source of dynamics in our estimated model is the unobserved heterogeneity in the job destruction rate; and the data show that a two-type heterogeneity may not be sufficient to fit the decreasing trend in the nonemployment inflow.

A model with a constant wage offer distribution for the entire sample period and constant wage growth on-the-job fits very well the eighteen years of mean hourly wage growth from about 8 to 16 dollars (Figures 10), with job mobility explaining about one third of such growth. The upward trend in the hourly wage variance is also well predicted by the model (Figure 11). Furthermore, the conditional moments of the model do well in predicting the mean and variance of wages below the minimum wage (Figures 12 and 13). The unconditional moments fit the trends in the data but do not fit as well the levels and seasonal fluctuations in wages.

Figure 14 presents model and data moments for the proportion of individuals working below the minimum wage. In estimation we have used the unconditional prediction of the model as the conditional moments have no information on the noncompliance parameter, α. A model with an exogenous, constant noncompliance parameter provides a very good fit of the level and trend of the proportion of workers paid below the minimum wage.[14]

As the estimated model predicts well the proportion of workers earning less than the minimum wage, it can provide a sound basis to illustrate the implications of changes in the compliance rate

[13] An extension that endogenizes δ would be beyond the scope of this paper and would not alter the substance of our model.

[14] If anything, one should note that such proportion is slightly overstated by our estimates towards the end of the sample period, and thus our model fit may be possibly improved by expressing α as an increasing function of the ratio of the minimum wage to the average wage in the economy. This ratio is clearly falling over time in our sample, and thus may deliver a lower value of α for the later years.

on labor market outcomes.

The cycle moments used in estimation are also reproduced well by our estimates (see Table 5). Mainly the mean duration, mean wage and standard deviation of the wage (above and below the minimum wage) are captured quite well by the model for cycle one and somewhat less accurately for the other two cycles. The model fits nonemployment duration and duration of each job in the cycles, as well as the mean and standard deviation of wages by jobs and cycles, both overall and below the minimum wage. The fit for the proportion of workers below the minimum wage is good in the first cycle but not as good for the second and third jobs in the later two cycles. This maybe somewhat explained by the low number of observations in later jobs/cycles.

The fit of transition moments is less accurate as it can be noted from the last three rows in Table 5. In particular, the model predicts a much higher transition rate from nonemployment to work in all three cycles. Job-to-job transitions also deviate from the data but to a lesser extent.

5.3 Counterfactual Policies

We finally use our estimated model to get quantitative implications of changing the level of the minimum wage (Table 6) and the rate of noncompliance with the minimum wage (Table 7).

The impact of an increase in the minimum wage can be assessed comparing figures in columns 3 and 4 of Table 6. From the first panel in the Table, an increase in the minimum wage by \$1.35, from \$5.15 to \$6.50, corresponding to a 26% increase, raises nonemployment by 0.6-1.1 percentage points, depending on labor market experience. According to our model, this comes from a combination of lower job offer arrival rates and (ambiguous) changes in the reservation wage. However, empirically we find that w_M has a negligible impact on w^*. Thus the increase in nonemployment driven by the increase in the minimum wage is almost entirely driven by the fact that $(1-\alpha)\left[F(w'_M) - F(w_M)\right]$ firms leave the market, where w'_M is the new value of the minimum wage.

The estimated elasticity of the nonemployment rate to the minimum wage, computed in correspondence of this increase, is around 0.3. This is an average across the estimated values of such elasticities across all years of experience. A similar comparison between column 3 and column 5 of Table 6 illustrates the effects of a 26% fall in the minimum wage, delivering a fall in nonemployment of 0.7-1.1 percentage points, depending on labor market experience, and the corresponding elasticity is 0.21. Such elasticities are typically lower than values reported in early studies of minimum wage employment effects (see Kennan 1995, 1998 and references therein). These elasticities are obtained under the assumption that firms' wage offers represent underlying productivity of jobs, and thus could be interpreted as an upper bound for the employment effect of minimum wages in the general case in which firms have some monopsony power and thus offer wages below productivity.

It should be finally noted that our estimates are obtained in correspondence of an elasticity of the meeting technology between workers and firms with respect to job seekers equal to 0.5, for which there is large support. We also performed some sensitivity analysis with respect to alternative values of η, looking at the employment effects of the same changes in the minimum wage as those

Table 5: Cycle moments in the data and estimated model

		Cycle One				Cycle Two				Cycle Three			
		NE	Job 1	Job 2	Job 3	NE	Job 1	Job 2	Job 3	NE	Job 1	Job 2	Job 3
Mean Duration	data	8.07	33.96	40.89	35.87	7.16	25.06	27.02	23.33	6.45	21.41	28.05	19.98
(months)	(model)	(8.15)	(24.03)	(29.41)	(32.27)	(7.49)	(24.80)	(26.97)	(23.38)	(6.50)	(20.04)	(19.99)	(18.48)
Mean Wage	data		8.22	10.37	11.85		10.22	11.02	11.49		9.95	11.29	11.81
(2000 dollars)	(model)		(9.78)	(12.31)	(13.57)		(10.71)	(12.44)	(12.97)		(9.79)	(11.24)	(11.99)
S.D. Wage	data		3.43	4.28	8.82		7.50	5.48	5.97		5.25	6.18	6.07
	(model)		(4.51)	(4.78)	(4.69)		(4.60)	(4.97)	(5.23)		(4.56)	(4.72)	(4.88)
Mean wage below w_M	data		4.89	5.17	4.99		4.99	4.96	3.47		4.29	4.72	5.02
(2000 dollars)	(model)		(4.46)	(4.92)	(5.27)		(4.36)	(4.96)	(5.16)		(4.13)	(4.70)	(4.06)
S.D. Wage Below w_M	data		1.38	1.21	1.35		1.20	1.17	1.10		1.56	0.85	1.00
	(model)		(1.01)	(0.90)	(1.34)		(1.06)	(0.90)	(1.06)		(0.95)	(0.78)	(1.00)
Proportion (%)	data		21.90	6.77	1.52		15.11	7.30	8.33		10.33	8.00	5.63
below w_M	(model)		(22.69)	(5.24)	(1.65)		(14.85)	(4.24)	(2.07)		(16.85)	(4.14)	(1.14)
	data	32.93*				71.58**				51.82**			
	(model)	(33.89)				(92.09)				(77.38)			
% moving from	data		51.74				52.07				50.88		
job 1 to job 2	(model)		(58.70)				(38.64)				(38.11)		
% moving from	data			54.55				48.76				55.86	
job 2 to job 3	(model)			(39.76)				(25.84)				(27.80)	

* The proportion of non-employed workers in cycle one.

** The proportions of workers moving to work from non-employment.

studied in Table 6. Setting $\eta = 0.3$ yields changes in the nonemployment rate between 0 and 0.8 percentage points. When $\eta = 0.7$, the implied changes in nonemployment are in the range of 0.9-1.4.[15] Our estimated results are thus not too sensitive to the adopted parameter value of η.

Table 6 also reports the estimated impact of changes in the minimum wage on a number of moments of the wage distribution. As expected, the increase in the minimum wage raises mean wages, as shown in panel 2 of the Table, but the corresponding elasticity is fairly low, around 0.12. Inequality, as measured by the 90 to 10 percentile wage ratio, is also reduced (panel 3). Finally, panel 4 shows that an increase in the minimum wage substantially increases the proportion of workers paid below the minimum wage. This model thus explains how important changes in the minimum wage generates also large changes in the proportion of workers paid below the minimum wage, with very modest changes in both the nonemployment rate and the wage distribution above the minimum wage.

The labor market effects of changing the noncompliance rate α are sort of symmetric to the effects of changing the minimum wage. These are reported in Table 7 for the estimated value of $\alpha \simeq 0.25$ and alternative values $\alpha = 0, 0.5, 1$. Removing noncompliance completely, i.e. going from $\alpha = 0.25$ to $\alpha = 0$ raises the nonemployment rate by 2 percentage points on average. Similarly, the hourly mean wage increases slightly and the 90 to 10 percentile wage ratio decreases slightly. The proportion of workers paid below the minimum wage obviously drops to zero after 2 years in the labor market. The reason why this proportion may not be zero upon labor market entry lies in the existence of a pre-graduation labor market, which is not subject to the minimum wage, and to measurement error.

6 Conclusions

This paper is an attempt to explain monthly work trajectories of white male high school graduates using a continuous time search model with both nonemployed and employed job search and minimum wages. We extended an otherwise conventional job search model by considering imperfect compliance to minimum wage regulations, and this is supposed to cater for the fact that early in their careers a large fraction of individuals in our sample are observed to earn less than the federal minimum wage. We interpret such wage observations as the result of either noncompliance (or exemptions) to the minimum wage, or measurement error, and separately identify the two factors by exploiting their different impact on labor transitions.

We have assumed that firms offer wages that reflect their idiosyncratic productivity, and thus firms whose productivity falls below the minimum wage either exit the market or choose not to comply. In this scenario a binding minimum wage reduces the arrival rate of job offers and has an ambiguous (though small) impact on both the reservation wage and the acceptance rate. Em-

[15] We have also obtained results for the extreme case $\eta = 1$, where job arrival rates are proportional to the number of firms. The estimated parameters of the wage distribution and α are very close to those reported in Table 4. The employment effects of changing the minimum wage are in the range of 1.3-2.1 percentage points.

Table 6: The effect of changes in the minimum wage

All individuals	Years in The Labor Market	Model $w_M = 5.15$	Counterfactuals $w_M = 6.5$	$w_M = 3.8$
Non-employment	1	26.2	27.1	25.1
rate	2-4	14.5	15.1	13.8
(by years in the	5-9	11.4	12.2	10.4
the labor market)	10-18	11.3	12.4	10.4
Mean wage	1	9.2	9.4	8.9
(in 2000 dollars)	2-4	11.5	11.9	11.0
	5-9	13.2	13.6	12.7
	10-18	14.9	15.4	14.3
90/10 percentile	1	3.0	3.2	3.1
wage ratio	2-4	2.9	2.8	3.3
	5-9	3.4	3.1	3.8
	10-18	4.1	3.7	4.5
% below the	1	12.5	21.4	4.4
minimum wage	2-4	4.6	10.2	1.5
	5-9	4.0	8.7	1.4
	10-18	4.2	9.0	1.4

Table 7: The effect of changes in compliance to the minimum wage

All individuals	Years in The Labor Market	Model $\alpha = 0.25$	$\alpha = 0$	Counterfactuals $\alpha = 0.5$	$\alpha = 1.0$
Non-employment	1	21.4	23.3	20.1	18.2
rate	2	10.7	12.7	9.4	7.9
(by years in the	5-9	9.8	11.7	8.6	7.1
the labor market)	10-18	9.9	11.8	8.7	7.1
Mean wage	1	9.2	9.3	9.1	8.9
(in 2000 dollars)	2	10.3	10.6	10.1	10.0
	5-9	12.8	13.1	12.6	12.4
	10-18	15.0	15.3	14.8	14.5
90/10 percentile	1	2.9	2.7	3.1	3.2
wage ratio	2	2.8	2.6	3.0	3.2
	5-9	3.4	3.1	3.6	4.0
	10-18	4.1	3.7	4.4	4.9
% below the	1	12.5	9.0	14.8	17.8
minimum wage	2	6.8	2.2	9.8	12.7
	5-9	4.9	0.0	7.9	11.2
	10-18	4.9	0.0	7.9	11.6

ployment effects of the minimum wage (and compliance parameters) thus mostly stem from their impact on the arrival rate of job offers.

We estimated this model by simulated methods of moments using the NLSY79. The number of parameters to be estimated was modest relatively to empirical dynamic stochastic models that attempt to provide an interpretation of the same data (see for example, Keane and Wolpin, 1997). Our parameter estimates predict a rate of noncompliance around 25%, and imply that job search and mobility explain between one third and a half of total wage growth in the first 18 years of labor market experience.

The estimated model fits well individual transitions from school to work, job-to-job transitions, and wage growth. It fails though to fit the declining trend in the nonemployment inflow, and this is due to one of our simplifying assumptions, namely an exogenous and constant job destruction rate along workers' careers. Overall, this paper has shown that a simple model with heterogeneous firms does quite a good job at replicating the observed labor supply and wage data. The main remaining question is whether it would also be capable of fitting firm level data, something for which matched employer-employee data should be advocated.

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Appendix A: Computation of $V_e'()$

Let $x(\alpha, w_M) = [1-(1-\alpha)F(w_M)]^{-(1-\eta)}$. Using integration by parts, (2) and (3) can be rewritten as:

$$\begin{aligned} rV_e(w_\tau) &= w_\tau + gw_\tau V_e'(w_\tau) + \delta\left[V_n - V_e(w_\tau)\right] \\ &\quad + x(\alpha, w_M)\lambda_e \int_{w_\tau} [1-F(w)] V_e'(w)\,dw \text{ for } w_\tau \geq w_M \end{aligned} \tag{7}$$

and

$$\begin{aligned} rV_e(w_\tau) &= w_\tau + gw_\tau V_e'(w_\tau) + \delta\left[V_n - V_e(w_\tau)\right] + x(\alpha, w_M)\left[\int_{w_M} [1-F(w)] V_e'(w)\,dw\right. \\ &\quad \left. + \int_{w_\tau}^{w_M} [1-\alpha F(w) - (1-\alpha)F(w_M)] V_e'(w)\,dw\right] \text{ for } w_\tau < w_M \end{aligned} \tag{8}$$

Differentiating (7) and (8) with respect to w_τ yields:

$$gw_\tau V''(w_\tau) = \left\{r + \delta + x(\alpha, w_M)\lambda_e\left[1 - F(w_\tau)\right] - g\right\} V'(w_\tau) - 1, \text{ for } w_\tau \geq w_M \tag{9}$$

$$gw_\tau V''(w_\tau) = \left\{r + \delta + x(\alpha, w_M)\lambda_e\left[1 - \alpha F(w_\tau) - (1-\alpha)F(w_M)\right] - g\right\} V'(w_\tau) - 1, \text{ for } w_\tau < w_M \tag{10}$$

Consider the case $w_\tau \geq w_M$ first, and let $u(w_\tau) = -\frac{1}{gw_\tau}\left\{r + \delta - g + x(\alpha, w_M)\lambda_e\left[1 - F(w_\tau)\right]\right\}$ and $q(w_\tau) = -\frac{1}{gw_\tau}$. Equation (9) implies

$$\begin{aligned} V_e'(w_\tau) &= e^{-\int u(w_\tau)dw_\tau}\left[A + \int q(w_\tau)e^{\int u(w_\tau)dw_\tau}dw_\tau\right] \\ &= e^{-\int_{w_0}^{w_\tau} u(s)ds}\left[A + \int_{w_0}^{w_\tau} q(s)e^{\int_{s_0}^{s_\tau} u(z)dz}ds\right], \end{aligned} \tag{11}$$

where A is an arbitrary constant. Now let

$$\begin{aligned} R(w_\tau; w_0) &= -\int_{w_0}^{w_\tau} u(s)ds \\ &= \int_{w_0}^{w_\tau} \frac{r + \delta - g + x(\alpha, w_M)\lambda_e[1 - F(s)]}{gs}ds. \end{aligned} \tag{12}$$

This in turn implies

$$\int_{w_0}^{w_\tau} q(s)e^{\int_{s_0}^{s_\tau} u(z)dz}ds = \int_{w_0}^{w_\tau} q(s)e^{-R(s)}ds = -\int_{w_0}^{w_\tau} \frac{1}{gs}e^{-R(s)}ds.$$

Having set $\tau = 0$ in (11), one obtains $V_e'(w_0) = A = \int_{w_0}^{\infty} \frac{1}{gs}e^{-R(s)}ds$ and thus

$$\begin{aligned} V_e'(w_\tau) &= e^{R(w_\tau)}\left[\int_{w_0}^{\infty} \frac{1}{gs}e^{-R(s)}ds - \int_{w_0}^{w_\tau} \frac{1}{gs}e^{-R(s)}ds\right] \\ &= e^{R(w_\tau)}\int_{w_\tau}^{\infty} \frac{1}{gs}e^{-R(s)}ds \\ &= \int_{w_\tau}^{\infty} \frac{1}{gs}e^{R(w_\tau)-R(s)}ds, \end{aligned}$$

where

$$R(w_\tau) - R(s) = \int_s^{w_\tau} \frac{r + \delta - g + x(\alpha, w_M)\lambda_e[1 - F(z)]}{gz} dz.$$

Therefore:

$$V_e'(w_\tau) = \int_{w_\tau}^{\infty} \frac{1}{gs} \exp\left(\int_s^{w_\tau} \frac{r + \delta - g + x(\alpha, w_M)\lambda_e[1 - F(z)]}{gz} dz \right) ds, \tag{13}$$

is the solution for $w_\tau > w_M$.

Similarly, when $w_\tau < w_M$

$$V_e'(w_\tau) = \int_{w_\tau}^{\infty} \frac{1}{gs} \exp\left(\int_s^{w_\tau} \frac{r + \delta - g + x(\alpha, w_M)\lambda_e[1 - \alpha F(z) - (1-\alpha) F(w_M)]}{gz} dz \right) ds. \tag{14}$$

Appendix B: Moments

Monthly Moments We use following formulas to compute monthly moments ($\tau = 1, 2, \cdots, 216$) in the data. Let mne^D be the vector of monthly nonemployment rates. Each of its element, $mne^D(\tau)$, is determined by

$$mne^D(\tau) = \frac{\sum_i I(d_{i\tau}^D = 0)}{\sum_i I(d_{i\tau}^D = 0) + \sum_i I(d_{i\tau}^D = 1)}.$$

$I(\cdot)$ is an indicator function, which equals one if the condition is satisfied and equals zero otherwise. Similarly the transition rates from nonemployment to employment are given by

$$mtr_1^D(\tau) = \frac{\sum_i I(d_{i\tau}^D = 0, d_{i\tau+1}^D = 1)}{\sum_i I(d_{i\tau}^D = 0)}, \tau = 1, 2, \cdots, 215.$$

Other transition rates are defined accordingly. Means and standard deviations of monthly wage are calculated according to

$$mw_1^D(\tau) = \frac{\sum_i (w_{i\tau}^D | w_{i\tau}^D > 0)}{\sum_i I(d_{i\tau}^D = 1 | w_{i\tau}^D > 0)}; mw_2^D(\tau) = \sqrt{\frac{\sum_i ((w_{i\tau}^D - mw_1^D(\tau))^2 | w_{i\tau}^D > 0)}{\sum_i I(d_{i\tau}^D = 1 | w_{i\tau}^D > 0) - 1}}.$$

The wage moments below the minimum wage use the same formulas for wage observations below the minimum wage, $w_{M\tau}$. Finally the proportion of working below the minimum wage is

$$mp^D(\tau) = \frac{\sum_i I(w_{i\tau}^D < w_{M\tau} | w_{i\tau}^D > 0)}{\sum_i I(d_{i\tau}^D = 1 | w_{i\tau}^D > 0)}.$$

Simulated moments are defined similarly for each simulation S and we take average over $N^s = 25$ simulations. For example simulated monthly nonemployment rates are defined as

$$mne^S(\tau) = \frac{1}{N^S} \sum_{s=1}^{N^S} \frac{\sum_i I(d_{i\tau}^s = 0)}{\sum_i I(d_{i\tau}^s = 0) + \sum_i I(d_{i\tau}^s = 1)}.$$

Simulated transition moments are defined both as one-period-ahead conditional moments and unconditional moments. The conditional moments make the predictions conditional on last year's *observed* data:

$$mtr_1^S(\tau) = \frac{1}{N^S}\sum_{s=1}^{N^S}\frac{\sum_i I(d_{i\tau}^D = 0, d_{i\tau+1}^s = 1)}{\sum_i I(d_{i\tau}^D = 0)}, \tau = 1, 2, \cdots, 215,$$

while the unconditional ones make the predictions based on last year's *simulated* data:

$$mtr_1^S(\tau) = \frac{1}{N^S}\sum_{s=1}^{N^S}\frac{\sum_i I(d_{i\tau}^s = 0, d_{i\tau+1}^s = 1)}{\sum_i I(d_{i\tau}^s = 0)}, \tau = 1, 2, \cdots, 215.$$

Cycle Moments Recall the way we construct employment cycles. To calculate the empirical moments, we follow each individual i for the first three cycle and the first three jobs in each cycle, i.e. $\{c_i^1(ne_i^1, J1_i^1, J2_i^1, J3_i^1), c_i^2(ne_i^2, J1_i^2, J2_i^2, J3_i^2), c_i^3(ne_i^3, J1_i^3, J2_i^3, J3_i^3)\}$. We convert our monthly data $[d_{i\tau}^D, w_{i\tau}^D]$ into $[\overline{d}_{it}^{Dcj}, \overline{w}_i^{Dcj}]$ where i denotes individual i, $c = 1, 2, 3$ denotes the number of cycle, $j = 0, 1, 2, 3$ corresponds to nonemployment, the first, second, and third job, t is the tenure on each job (or nonemployment). For example $\overline{d}_{i10}^{12} = 1$ means individual i works (otherwise equals 0) in the 10th month on the second job of his first employment cycle and $\overline{d}_{i5}^{20} = 1$ denotes fifth month nonemployment in the second cycle. $\overline{w}_i^{Dcj}$ presents the accepted wage for job j in cycle c, which is the first wage observation on the job.

Data cycle moments are defined as following. Duration of cycle c job j for individual i is $\sum_t \overline{d}_{it}^{cj}$, thus mean duration

$$mdur^{Dcj} = \frac{\sum_i(\sum_t \overline{d}_{it}^{Dcj})}{\sum_i I(\sum_t \overline{d}_{it}^{Dcj} \geq 1)}, c = 1, 2, 3, j = 0, 1, 2, 3.$$

Means and standard deviations of accepted wage are computed as

$$mwage_1^{Dcj} = \frac{\sum_i(\overline{w}_i^{Dcj}|\overline{w}_i^{Dcj} > 0)}{\sum_i I(\overline{d}_{i1}^{Dcj} = 1|\overline{w}_i^{Dcj} > 0)}, stdwage_1^{Dcj} = \sqrt{\frac{\sum_i((\overline{w}_i^{Dcj} - mwage_1^{Dcj})^2|\overline{w}_i^{Dcj} > 0)}{\sum_i I(\overline{d}_{i1}^{Dcj} = 1|\overline{w}_i^{Dcj} > 0) - 1}}, c, j = 1, 2, 3.$$

Wage moments below the minimum wage are defined similarly. The proportion of workers paid below the minimum wage on job j in cycle c is

$$prop^{Dcj} = \frac{\sum_i I(\overline{w}_i^{Dcj} < w_{M\tau}|\overline{w}_i^{Dcj} > 0)}{\sum_i I(\overline{d}_{i1}^{Dcj} = 1|\overline{w}_i^{Dcj} > 0)}, c, j = 1, 2, 3.$$

The proportion of workers start cycle c as nonemployed is

$$ne^{Dc} = \frac{\sum_i I(\overline{d}_{i1}^{Dc0} = 1)}{577}, c = 1, 2, 3.$$

The proportions of workers move from job 1 to job 2, and from job 2 to job 3 in cycle c are

$$tr_1^{Dc} = \frac{\sum_i I(\overline{d}_{i1}^{Dc1} = 1, \overline{d}_{i1}^{Dc2} = 1)}{\sum_i I(\overline{d}_{i1}^{Dc1} = 1)}, \text{ and } tr_2^{Dc} = \frac{\sum_i I(\overline{d}_{i1}^{Dc2} = 1, \overline{d}_{i1}^{Dc3} = 1)}{\sum_i I(\overline{d}_{i1}^{Dc2} = 1)}, \ c = 1, 2, 3.$$

Like monthly moments, simulated cycle moments are defined for each simulation S and we take average over $N^s = 25$ simulations.

Figure 1: Monthly Employment and Nonemployment Rates

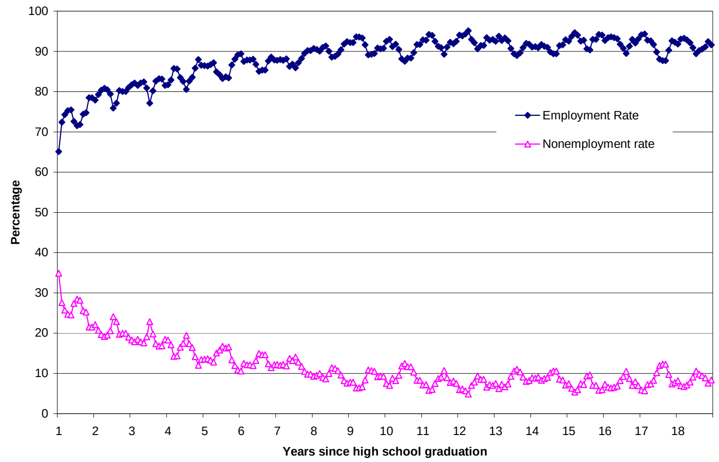


Figure 2: Job Separation Rate by Job Tenure (Months)

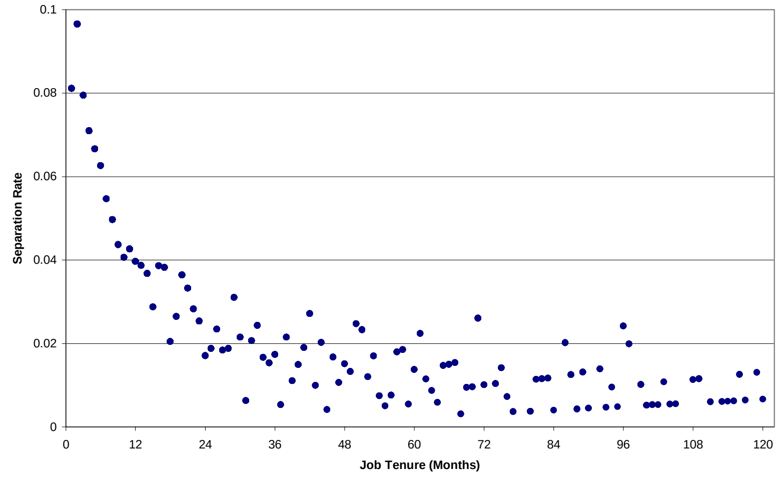


Figure 3: Transition Probabilities From and To Employment and Nonemployment

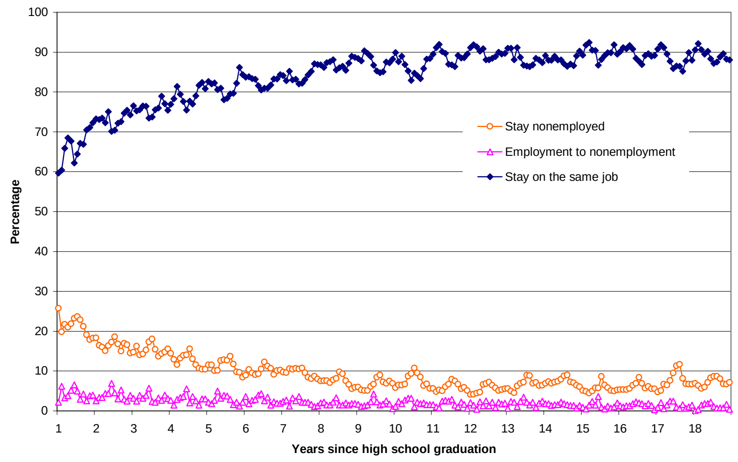


Figure 4: Transition Probabilities from Job to Job and from Nonemployment to Employment

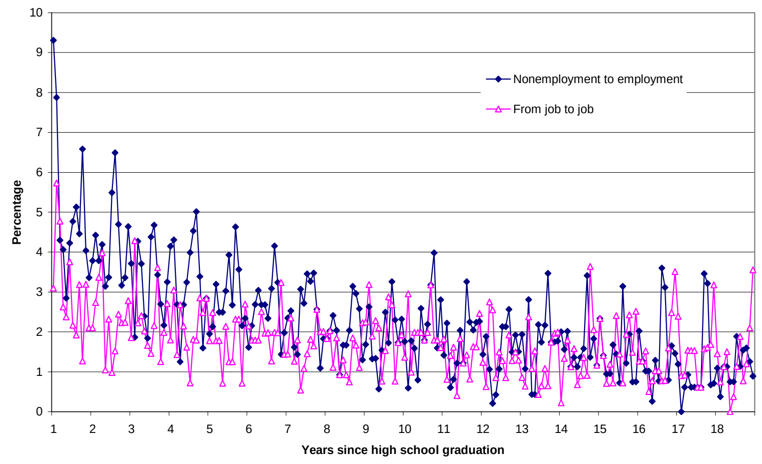


Figure 5: Federal Minimum Wage Under the Fair Labor Standards Act

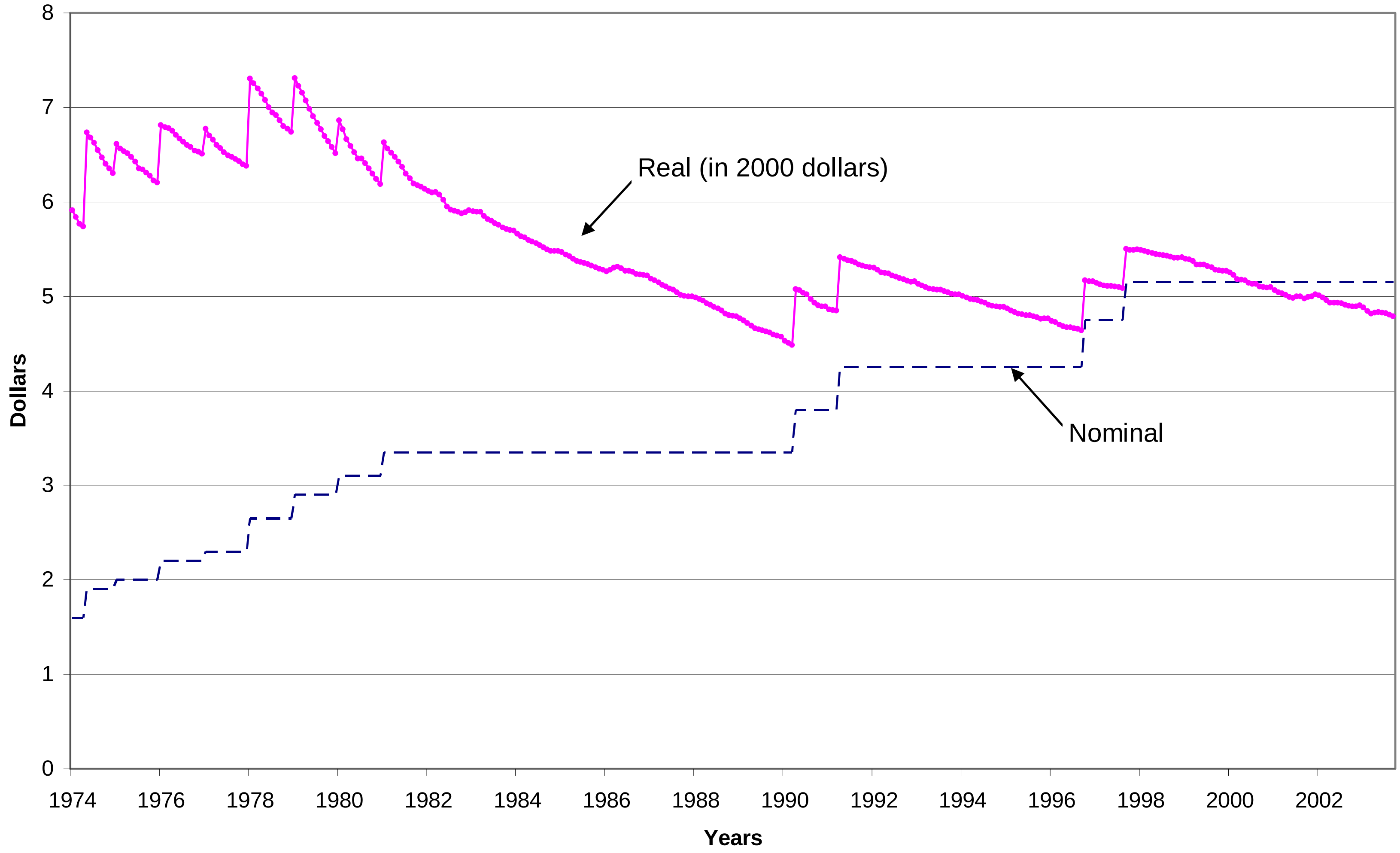


Figure 6: Actual and Predicted Monthly Nonemployment Rate

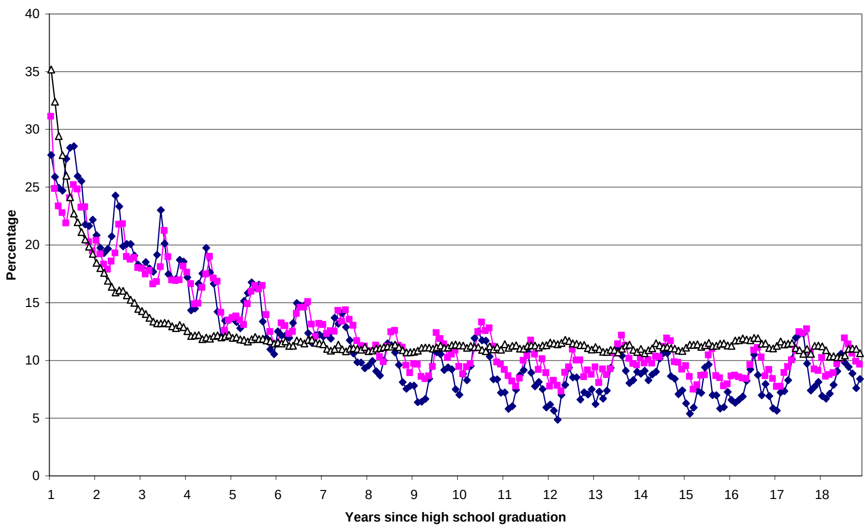


Figure 7: Actual and Predicted Monthly Transition Rate from Nonemployment to Work

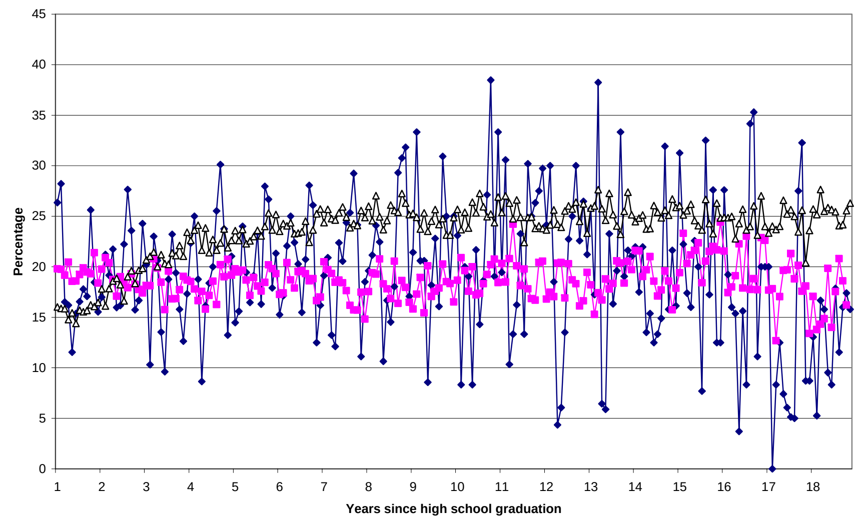


Figure 8: Actual and Predicted Monthly Transition Rate from Job-to-job

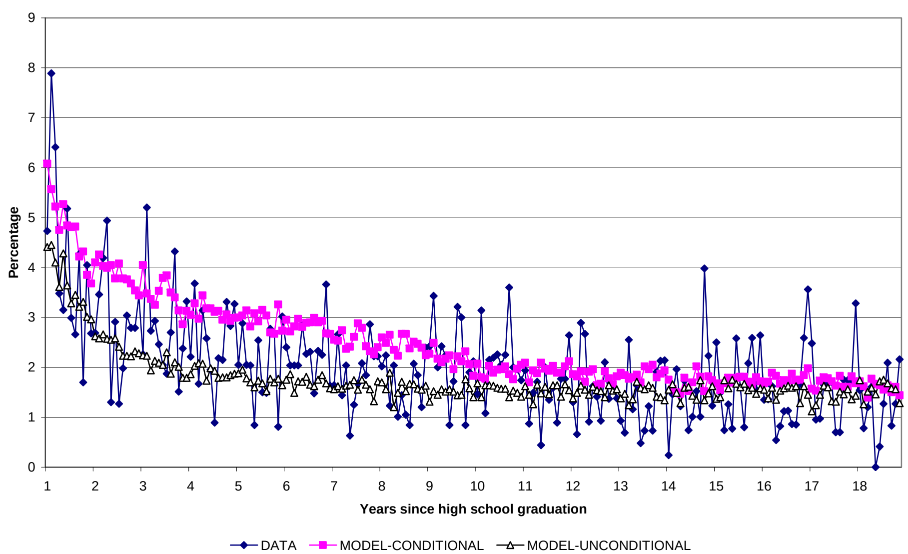


Figure 9: Actual and Predicted Monthly Transition Rate from Employment to Nonemployment

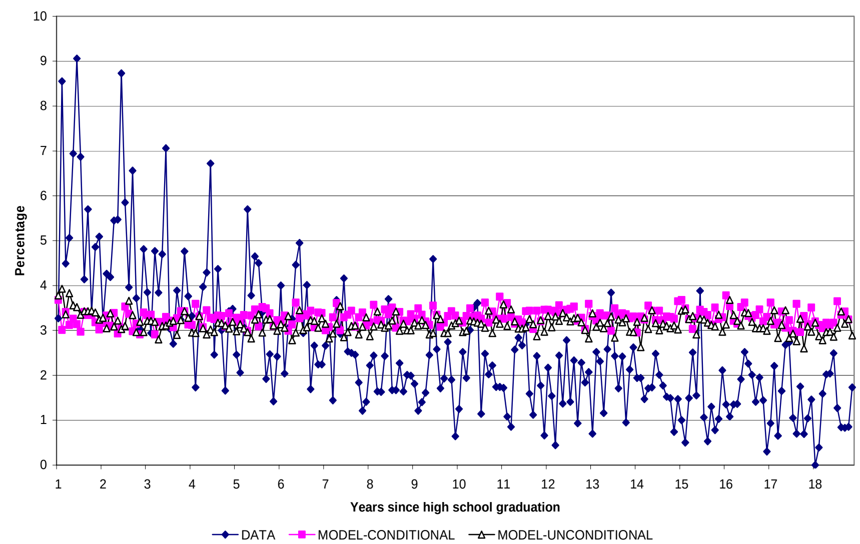


Figure 10: Actual and Predicted Hourly Mean Wage

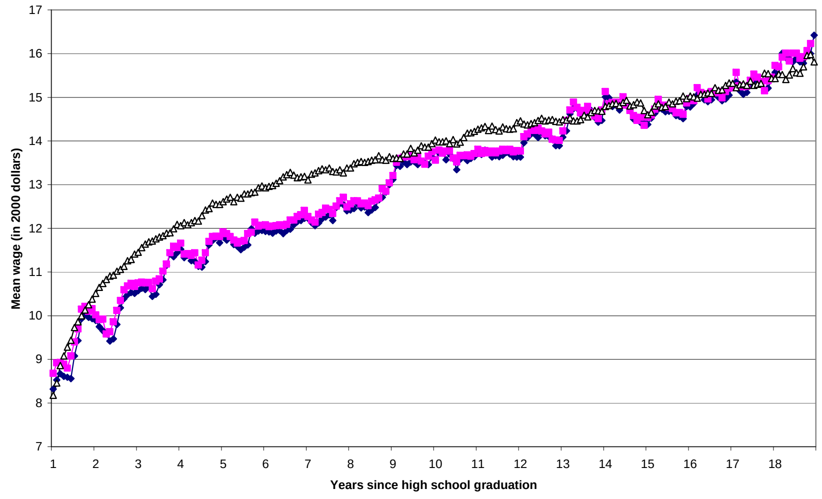


Figure 11: Actual and Predicted Standard Deviation of Hourly Wage

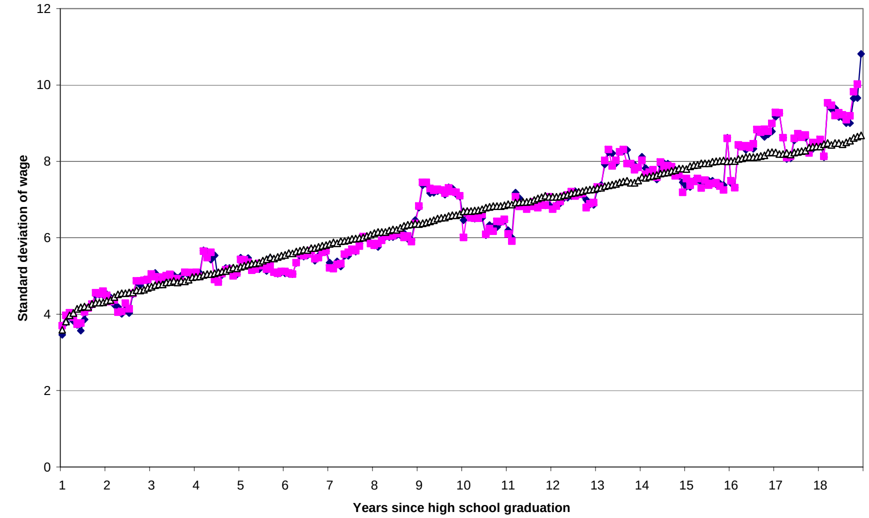


Figure 12: Actual and Predicted Hourly Mean Wage Below the Minimum Wage

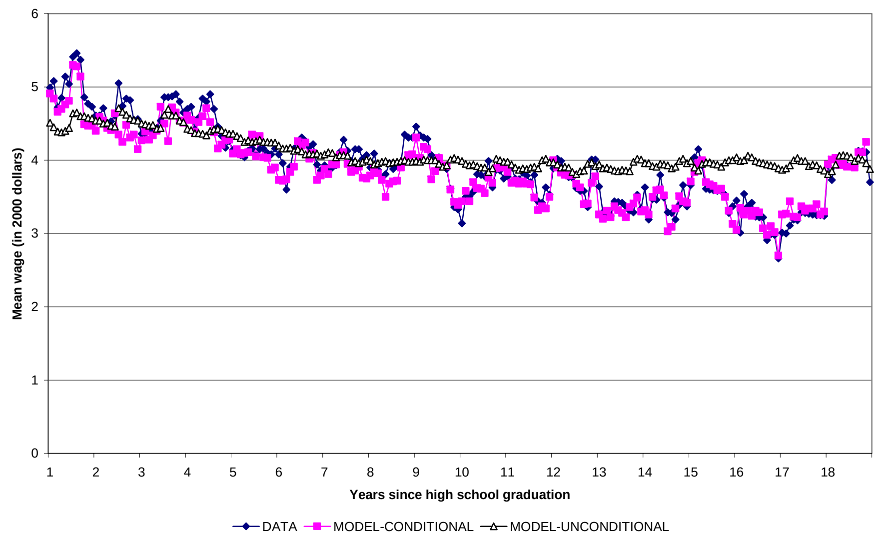


Figure 13: Actual and Predicted Standard Deviation of Hourly Wage Below the Minimum Wage

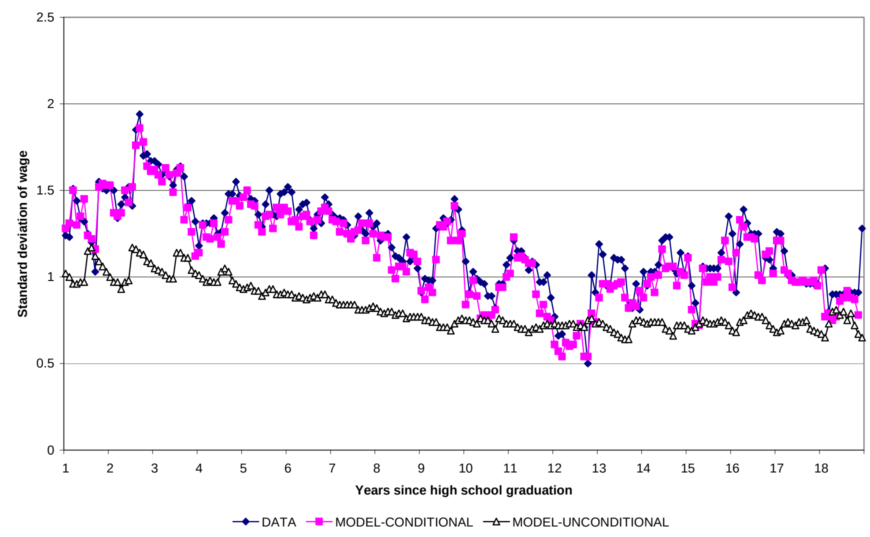
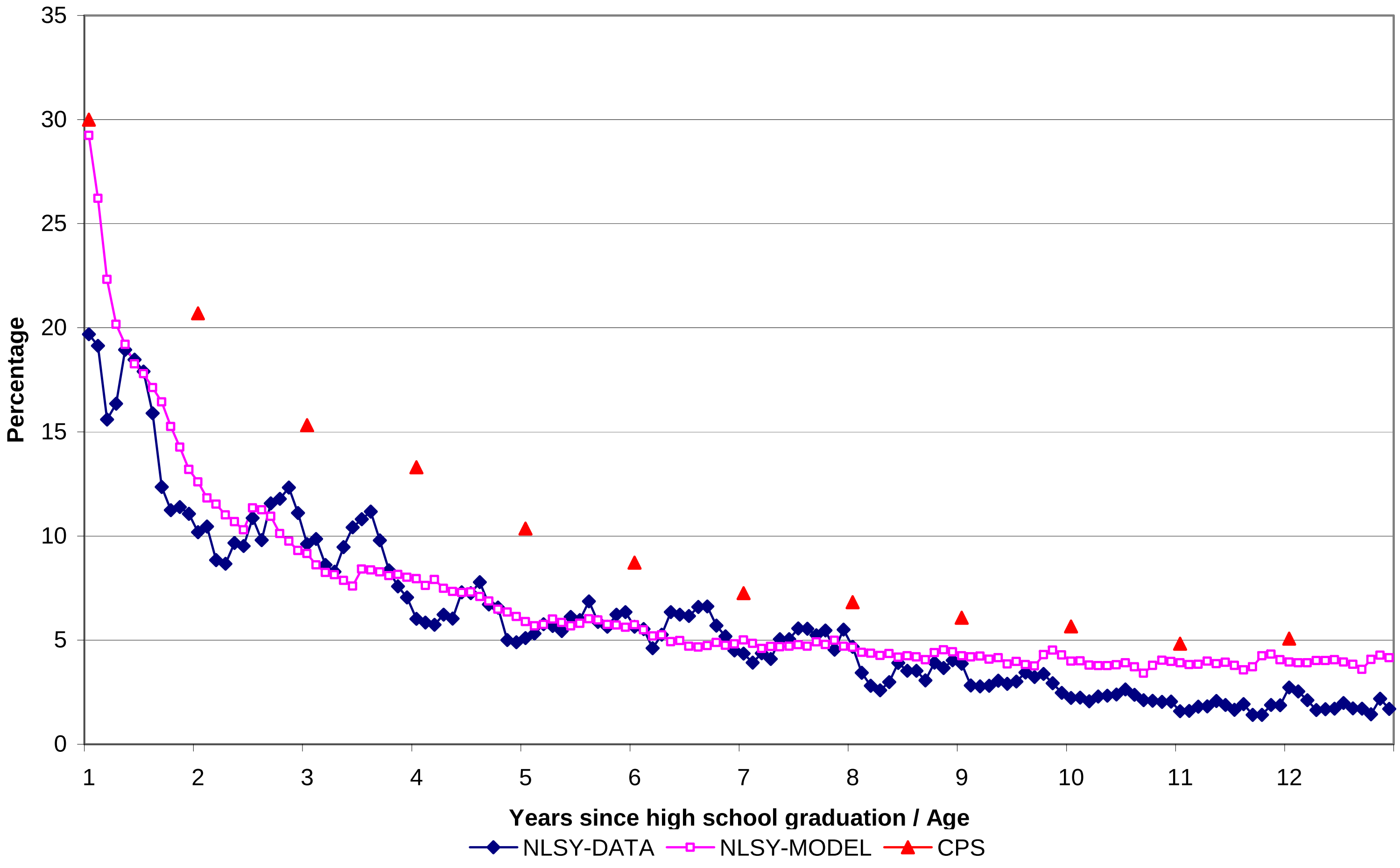


Figure 14: Percentage of workers paid below the minimum wage



Note: CPS Wage data has the same restrictions as for NLSY wage data. We calculate the mean of the proportions of workers paid below the minimum wage between 1979-1997 for youth aged between 19 to 36.