Economic Conditions and Earnings Over the Lifecycle*

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Abstract

Previous studies suggest that the negative effect of adverse economic conditions on wages might vary with experience level. This paper estimates the effect of economic conditions on expected lifetime earnings at different stages of a career. A non-stationary partial-equilibrium search model with static expectations is estimated using the matched Current Population Survey March Supplements, 1980-2010. Change in economic conditions is identified by variation of the model parameters over time. I find that adverse economic conditions have greater negative effect on expected lifetime earnings if they occur early in a worker's career. For workers with high school degrees or less, experience of the worst economic conditions during the sample period for five years could lead to a 6% decline in expected lifetime earnings if the adverse experience happens at labor market entry; and the decline is only 3% if the adverse experience happens after 20 years in the labor market. Magnitude of the negative effect on expected lifetime earnings decreases with education, and most of the negative effect could be explained by variation of employment transitions over the business cycle rather than variation of earning mobility.

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1 Introduction

Variation of economic conditions over the business cycle can have long-term effect on earnings. An important question is whether younger workers or more experienced workers are hurt more by adverse economic conditions. Young workers tend to have greater employment and earnings mobility in their searches for good job matches. Adverse economic conditions early in one's career could slow down this beneficial job shopping process. If circumstances later in career make the catch-up slow or impossible, this slow-down in wage growth early in career might lead to significant losses in lifetime earnings. On the other hand, adverse economic conditions could lead to significant earnings losses for more experienced workers: the rate of involuntary job loss increases during adverse economic conditions, and the theory of job search and specific human capital imply a large decline in earnings at job displacement for more experienced workers. This study assesses the quantitative importance of lifecycle effect of economic conditions on expected lifetime earnings.

To illustrate the question, consider two groups of workers who remain in the labor market for 35 years. The first group of workers experience a weak economy or slack labor market for their first 5 years in the labor market and a normal labor market thereafter. The other group of workers experience the slack labor market for 5 years after they have been in the normal labor market for 20 years, and they experience the normal labor market thereafter. Even though the two groups of workers experience the same average labor market conditions over their careers, their total earnings over the 35 years are not necessarily the same if economic conditions interact with wage growth differently at different stages of a career. But how important is the effect of adverse economic conditions on lifetime earnings at different stages of a career?

The theory of job search suggests that the interaction between economic conditions and wage growth changes over the lifecycle. However, the theory can't answer the question how much the effect of economic conditions on wage growth varies with potential labor market experience (the use of experience refers to potential labor market experience hereafter). In the standard job search model, jobs are considered as "search goods": workers know the match quality at the start of the match, and matches of higher quality yield higher wages (Jovanovic (1979)). The model accounts for many labor market regularities. For example, a more experienced worker is more likely to be in a better job match, and less likely to change job due to a low arrival rate of a better outside offer; longer-tenured jobs tend to be higher-paying jobs because bad matches are more likely to end early; and involuntary job changes or job displacement will lead to wage decline due to the loss of "search capital".

The model of job search suggests earnings losses from adverse economic conditions for young workers . The basic job search model implies that the return to experience decreases with experience because a worker is less likely to receive a higher wage offer as his wage goes up with experience. Empirical studies confirm this prediction: wage growth and job mobility decrease with experience. In their seminal paper on wage growth for male high school graduates, Topel and Ward (1992) find that 66% of lifetime wage growth occurs in the first ten years of a career, and most of the growth comes from job-to-job mobility. This evidence suggests that job mobility early in career is important for young workers to attain a good match. If the wage growth comes from return to job search and adverse economic conditions impede the job search, the business cycle will affect the return of job search, therefore the rate of wage growth. Such disadvantage is further magnified by frictions in the labor market: it would take time for wages of these young workers to catch up with the other cohorts who don't experience adverse economic conditions early in career. The negative effect of adverse economic conditions early in career on lifetime earnings is expected to be large.

More experienced workers might have more to lose from adverse labor market conditions than young workers. Better matches are associated with higher tenure in the basic search model. Because the probability of being in a good match increases with experience, more experienced workers have longer tenure on average. This suggests that more experienced workers would have higher wages due to accumulated search capital. Accumulation of specific human capital would also imply that wages increase with tenure. So more experienced worker would have greater earnings losses at job displacement on average due to combined losses of search capital and specific human capital. Empirical studies show that experienced workers face large earnings losses at job displacement (Jacobson, et al. (1993)) and employment instability following the displacement (Stevens (1997)), and the magnitude of earnings losses increases with tenure on the pre-displacement job (Farber (2005)). The initial earnings losses (Jacobson, et al. (1993)) and the subsequent recovery (Eliason and Storrie (2006)) are sensitive to the business cycle. So the present value of earnings losses associated with job loss is higher if the job is lost during recessions (Davis and von Wachter (2011)). Moreover, the trough of a business cycle is usually associated with restructure of some sectors in the economy. A displaced worker might not be able find a job in the same industry or occupation of his previous job. He therefore faces additional earnings losses at job displacement due to the losses of industry- or occupation- specific human capitals (Neal (1995) and Parent (2000)). If the probability of job loss varies greatly with the business cycle and the earnings losses at job displacement are significant later in career, adverse economic conditions later in career would have a large negative effect on lifetime earnings.

Previous empirical studies have not offered a clear answer as to whether the effect of economic conditions on wage growth changes with experience. These studies have found persistent effect of economic conditions on wages at various stages of a worker's career. Following Bils (1985), these studies identify economic conditions with unemployment rates. The effect is estimated by comparing current or future wages of cohorts who enters the labor market at different time and assuming a parametric relationship between unemployment rates and average wages. Adverse economic conditions at the time of labor market entry have persistent negative effects on future wages (e.g. Bowlus and Liu (2003) document this for high school graduates in the US, Kahn (2010) for college graduates in the US, and Oreopoulos, et al. (2006) for college graduates in Canada.). For workers with some years of experience in the labor market, Beaudry and DiNardo (1991) find that the dependence of wages on the minimum unemployment rate since the start of the job is stronger than on the current unemployment rate. The empirical evidence of persistence suggests that the effect of economic conditions could have a large effect on lifetime earnings. Because each study only focuses on a group of workers with similar labor market experience levels, there is little empirical evidence on whether this persistent effect varies by experience.

The unemployment rate is a measure of stock at any given time. Since the focus of this study is the interaction of economic conditions and wage dynamics over a career, instead of using unemployment rates to identify economic conditions, a more direct way to study the dynamics is to look at how employment and wages transitions vary over the business cycle.

A job search model provides an appropriate empirical framework to study labor market transitions. Search frictions could account for the persistence in the effect of economic conditions on wages as found in the previous empirical studies. However, the parameters in a standard stationary job search model are fixed over time and therefore unsuitable for the study of economic conditions and earnings[1]. The non-stationary job search model used here follows from Bowlus and Robin (2004). The model is a discrete-time non-stationary search model with static expectations. It offers a parsimonious way to summarize job and earnings dynamics, and it can be estimated using a very short panel. The transition parameters and the earnings offer distributions in the model are allowed to vary with both time and observable characteristics.

An alternative non-stationary job search model is presented in Van den Berg (1990). It is a continuous-time model with infinite time horizon. The parameters of search frictions vary with time for a finite number of periods after unemployment, and the model becomes stationary thereafter. A direct application of the model is not suitable for the current study. The model focuses on non-stationarity for unemployed workers. Employed workers stay at the same job with the same wages forever: there is no on-the-job search. Allowing non-stationarity only for unemployed workers is insufficient for capturing the dynamics in the data.

In this paper, change in economic conditions is identified by variation of model parameters over time. The model parameters are estimated from worker flows between two consecutive periods and disaggregate earnings data at the two periods. The implicit assumption is that the economic conditions don't change too much over the two periods. The model parameters are also allowed to vary with experience levels to account for changes in mobility with experience. This specification is more general than the reduced-form analysis using unemployment rates to measure of economic conditions since I don't impose a parametric relationship between economic conditions and earnings growth.

The model also incorporates the implications of specific human capital. In the model, the parameters of earnings increase and decrease can account for the accumulation of job-specific human capital: compared to other workers in his cohort who stay employed, a worker with a spell of nonemployment loses the earnings gains or losses he had accumulated at the previous job. Another feature of the model in Bowlus and Robin (2004) is that both workers who are employed after a nonemployment spell and workers who stay employed draw earnings offers from the same distribution. But in addition to losing job-specific human capital at job displacement, a displaced

[1] Mortensen (1986) reviews the literature on the model of individual worker search decisions in which the wage offer distribution is exogenous. The model in this paper builds upon this framework. Later works on equilibrium job search model incorporate the decisions of employers on the demand side of the labor market (see Rogerson et. al (2005) for a review of the literature).

worker could also lose search capital he has accumulated since the beginning of his career and industry- or occupation-specific human capital. In this paper, employed workers and nonemployed workers draw their earnings offers from two different distributions if they are employed in the next period.

The non-stationary model is estimated using two-year panel data constructed from the Current Population Survey (CPS) March Supplements collected between 1980 and 2010. Using the estimated parameters, I simulate earnings trajectories for workers who have experienced different sequences of economic conditions. A worker is said to experience adverse economic conditions if his transitions are governed by estimated model parameters from the years with the worst economic conditions. Experience of positive economic conditions is defined similarly. A worker is said to experience normal economic conditions if his transitions are determined by the average parameters of years with neither the best nor the worst economic conditions. The ranking of years by economic conditions is based on two measures. The first measure is the expected lifetime earnings of a worker whose labor market transitions in each period of his career are determined by the set of model parameters from a particular year. The second measure is the average ex-ante welfare of workers in the sample of that year. Based on these two measures of economic conditions, the year with the worst economic conditions is 2008, and the years with the best economic conditions are 1997-1999.

I find that adverse economic conditions have the greatest negative effect on a worker's expected lifetime earnings if they occur early in his career. At the baseline, a worker experiences the normal economic conditions for his entire career. Given a 35-year career, experiencing the worst economic conditions for five years at labor market entry can reduce a worker's expected lifetime earnings by up to 6% compared to the baseline case; and experiencing the worst economic conditions for five years after 20 years in the labor market only reduces the expected lifetime earnings by up to 3%. The effect decreases with education. Employment mobility (transition in and out of employment) is more important for explaining the negative effect than earnings mobility (the arrival rates of earnings offers and the earnings offer distribution for continuously employed workers).

2 The Job Search Model

The behavioral model is a discrete-time partial equilibrium search model in a non-stationary environment with on-the-job search and static expectations. The model has infinite time horizon. Each individual remains in the labor market for a fixed number of periods. Consider an individual who has been in the labor market for a periods, where a can be any integer between 1 and the maximal year of experience A. In each period t, the worker can be either employed with a positive wage or nonemployed. In each period, nonemployed workers have a positive probability of transition into employment next period; and employed workers have a positive probability of becoming nonemployed next period or obtain different wages next period. The labor market transitions depend on a set of model parameters prevailing in the current period. In this non-stationary model, model parameters are allowed to change with time.

The model departs from the model in Bowlus and Robin (2004) by allowing employed workers and nonemployed workers to draw from different wage offer distributions. In both models, a worker who is employed in two consecutive periods has positive probability of having a wage increase or a wage decrease. The positive probability of wage changes in each period can account for accumulation of job-specific human capital. If the worker loses his current job, he would lose all the wages gains and losses that he has accrued at the displaced job. Empirical evidence also indicates the importance of industry- or occupation-specific human capitals. These will also be lost at job displacement if the worker could only find a job at a different industry or occupation. In addition to the loss specific human capitals, the theory of job search suggests that at job displacement the worker will also lose the search capital that he has accumulated through his time in the labor market. So the wage offer distribution should be correlated with a worker's tenure on the job, tenure in the current industry or occupation, and experience in the labor market.

However, in the sample, there is no information on tenure. Workers are only observed for two periods (more details in the data section). If a worker is observed transitioning from nonemployment to employment between the two consecutive periods, there is no information on his industry or occupation at his pre-displacement job. Even if a model with tenure and industry- or occupation-mobility can't be estimated due to sample restriction, the main implication from the theory of search and specific human capital can be incorporated into the model. The theory indicates that workers who have been continuously employed and workers who re-enter the work force after a spell of nonemployment should face different opportunities in the labor market. This difference in opportunities between the two groups of workers is captured by the different wage offer distributions. In the model, there is a positive probability of receiving a new wage offer for the both groups of workers, but the offers are drawn from two different distributions.

An individual knows the values of model parameters for the current period. In each period, he chooses among different offers based on their expected values, which in turn depend on his belief about future economic environment, i.e. values of model parameters in the subsequent periods. To model individual decisions, assumptions need to be made about his beliefs or expectations about the values of model parameters for the rest of his career. In the model, workers have static expectations: at time t, they observe θ_t and expect θ_τ to equal to θ_t for all $\tau > t$.

An individual of experience level a who is nonemployed at the beginning of period t receives some return of $b_{a,t}$ in period t. With probability $\lambda^0_{a,t}$, he receives a wage offer w_{t+1} drawn from the continuous wage offer distribution $F^0_{a,t}$ bounded between $\underline{w}^0_{a,t}$ and $\overline{w}^0_{a,t}$. The individual receives wage w_{t+1} in period $t+1$ if the offer is accepted. He will accept the offer if the expected present value of employment at this wage offer is greater than the expected present value of nonemployment in period $t+1$. He will remain in nonemployment in period $t+1$ if he rejects the offer. If he doesn't receive any offer in period t, he will also remain in nonemployment in period $t+1$.

An employed worker of experience level a faces the following decisions in period t. The employed worker receives a wage w_t at the beginning of period t. He becomes nonemployed in period $t+1$ with probability $\delta_{a,t}$. If the worker remains employed in period $t+1$, he experiences a reallocation shock. A wage w_{t+1} is drawn from a continuous wage offer distribution $F^1_{a,t}$ bounded between $\underline{w}^1_{a,t}$ and $\overline{w}^1_{a,t}$. If the wage draw w_{t+1} is higher than his current wage w_t, he is offered w_{t+1} for the next period with probability $\lambda^+_{a,t}(w_t)$; if the wage draw is lower than his current wage, he is offered w_{t+1} for the next period with probability $\lambda^-_{a,t}(w_t)$. The worker is offered his current wage w_t for the next period if he remains employed but neither a higher nor a lower wage offer arrives. The alternative to accepting a wage offer is to become nonemployed next period. So an optimizing worker will always accept the new wage offer as long as the wage offer yields a higher expected present value than nonemployment in period $t+1$.

To summarize the earnings dynamics of employed workers, the distribution of w_{t+1} conditional on w_t for an employed worker is the following:

- the density at $w_{t+1} > w_t$ is $\lambda^+_{a,t}(w_t) \cdot dF^1_{a,t}(w_{t+1})$,
- the density at $w_{t+1} < w_t$ is $\lambda^-_{a,t}(w_t) \cdot dF^1_{a,t}(w_{t+1})$,
- and the density at $w_{t+1} = w_t$ is $1 - \lambda^+_{a,t}(w_t) \cdot \left[1 - F^1_{a,t}(w_t)\right] - \lambda^-_{a,t}(w_t) \cdot F^1_{a,t}(w_t)$,

where $dF^1_{a,t}(\cdot)$ refers to the sampling probability measure for employed workers[2]. Note that the distribution of w_{t+1} conditional on w_t is absolutely continuous with respect to the sampling distribution $dF^1_{a,t}(w_{t+1})$ except at w_t. Empirically, the specification of negative reallocation shock can account for earnings decreases observed in the data.

The set of model parameters is $\theta_t = \{b_{a,t}, F^0_{a,t}, \delta_{a,t}, \lambda^0_{a,t}, \lambda^+_{a,t}(w), \lambda^-_{a,t}(w), F^1_{a,t}, a = 1, , ..., A\}$ for each period t. The model parameters can vary with experience level and time. Because this paper focuses on how the interaction between economic conditions and earnings varies over the life cycle, allowing the parameters to vary with experience will capture any changes in behaviors or responses to the business cycle over a worker's career. In addition, the parameters are allowed to vary with observable characteristics, such as education level. Variation in the model parameters with education level accounts for the heterogeneous effects of economic conditions on earnings by skill level. For a worker, the model parameters change over time; and every period, new workers are born. So workers are homogeneous given time period, labor market experience, and education.

Since the alternative to rejecting a wage offer is nonemployment, a worker will not accept a wage offer with lower expected future value than nonemployment. Facing with the optimizing workers, firms will not offer a wage that gives a lower present value than nonemployment, or $\underline{w}^0_{a,t}$ and $\underline{w}^1_{a,t}$ have expected values at least as great as nonemployment. A worker will always choose employment when he is indifferent between employment and nonemployment. Given the firms' wage policy, a nonemployed worker will always accept a wage offer; and an employed worker will never reject any wage offer even if the wage offer is below his current wage.

Given the assumption of static expectations and finite periods of working life, the only nonstationarity in the model is from aging, or increase in labor market experience. Workers' decisions

[2] The model differs from the standard job search model: job and wage changes are not modeled separately for workers who are employed in two consecutive periods. This is due to the lack of information on job changes in the data. In this application, it is sufficient to model wage changes because the focus of the study is wage dynamics.

can be expressed as a set of Bellman equations. Let $V_{a,t}$ denote the present value of nonemployment in period t for a worker with labor market experience level a, and let $W_{a,t}(w)$ denote the present value of employment at wage w in period t for a worker with experience level a. r is the interest rate. There is no retirement income, the terminal condition is given by

$$W_{A,t}(w) = V_{A,t} = 0. \tag{1}$$

The value of nonemployment consists of three components: the non-labor income, the expected value of finding a job next period, and the expected value of remaining in nonemployment next period. The Bellman equation for value of nonemployment is given by

$$(1+r)V_{a,t} = b_{a,t} + \lambda^0_{a,t} \int_{\underline{w}^0_t}^{\overline{w}^0_{a,t}} W_{a+1,t}(x) dF^0_{a,t}(x) + (1-\lambda^0_{a,t})V_{a+1,t}. \tag{2}$$

The value employment consists of four components: wages for the current period, the expected value of nonemployment next period, the expected value of wage changes next period (either a wage increase or decrease), and the expected value of remaining in the employment next period. The Bellman equation for value of employment at wage w is given by

$$\begin{aligned}(1+r)W_{a,t}(w) \quad = \quad & w + \delta_{a,t}V_{a+1,t} \\ & +\lambda^+_{a,t}(w) \int_{w}^{\overline{w}^1_{a,t}} W_{a+1,t}(x) dF^1_{a,t}(x) \\ & +\lambda^-_{a,t}(w) \int_{\underline{w}^1_t}^{w} W_{a+1,t}(x) dF^1_{a,t}(x) \\ & + \left[1 - \delta_{a,t} - \lambda^+_{a,t}(w)\left(1 - F^1_{a,t}(w)\right) - \lambda^-_{a,t}(w) F^1_{a,t}(w)\right] W_{a+1,t}(w).\end{aligned} \tag{3}$$

In the above Bellman equations, $V_{a+1,t+1}$ and $W_{a+1,t+1}(x)$ are replaced by $V_{a+1,t}$ and $W_{a+1,t}(x)$ under the assumption of static expectations.

In the model, $\underline{w}^1_{a,t}$ is allowed to vary with both experience level and time. Because workers who are employed in both periods t and $t+1$ have a positive probability of keeping the same wage, $\underline{w}^1_{a,t}$ should be independent of the experience level, i.e. $\underline{w}^1_{a,t} = \underline{w}^1_t$. In the Bellman equations, $\underline{w}^1_{a,t}$ and is replaced by $\underline{w}^1_t$ following this assumption. Similarly, workers who are employed in both periods t and $t+1$ following nonemployment in period $t-1$ have a positive probability of keeping the same wage, so $\underline{w}_t^0 = \underline{w}_t^1$. The same argument applies to the upper bounds of earnings offer distributions, i.e. $\overline{w}_{a,t}^1 = \overline{w}_{a,t}^0$.

The wage policy of the firm implies that any wage offer will yield higher present value than nonemployment, i.e., $W_{a,t}(\underline{w}_t^1) \geq V_{a,t}$. To identify non-labor income, $b_{a,t}$, from the wage data, the firms are assumed to have enough monopsony power to force the minimum wage offer $\underline{w}_t^1$, i.e. $W_{a,t}(\underline{w}_t^1) = V_{a,t}$. Equation (3) evaluated at $w = \underline{w}_t^1$ under the assumption implies

$$(1+r)V_{a,t} = \underline{w}_t^1 + \lambda_{a,t}^+(\underline{w}_t^1) \int_{\underline{w}_t^1}^{\overline{w}_{a,t}^1} W_{a+1,t}(x) dF_{a,t}^1(x) + \left(1 - \lambda_{a,t}^+(\underline{w}_t^1)\right) V_{a+1,t}. \tag{4}$$

Equations (2) and (4) yield the following expression for the non-labor income $b_{a,t}$

$$\begin{aligned} b_{a,t} \quad = \quad & \underline{w}_t^1 + \lambda_{a,t}^+(\underline{w}_t^1) \int_{\underline{w}_t^1}^{\overline{w}_{a,t}^1} W_{a+1,t}(x) dF_{a,t}^1(x) - \lambda_{a,t}^0 \int_{\underline{w}_t^0}^{\overline{w}_{a,t}^0} W_{a+1,t}(x) dF_{a,t}^0(x) \\ & - \left(\lambda_{a,t}^+(\underline{w}_t^1) - \lambda_{a,t}^0\right) V_{a+1,t}. \end{aligned} \tag{5}$$

Equations (3) and (4) can be solved backward given the terminal conditions (Equation 1) to obtain the values of employment and nonemployment.

3 Data

Longitudinal data with information on labor market status and earnings are required for estimating the transition probabilities and the offer distributions in the model. The CPS March Supplements contain relevant variables. The CPS is a monthly survey of the labor force in the US. About 60,000 households are interviewed for the survey each month. The March Supplements collect additional information on work and earnings in the previous calendar year. The CPS is a sample of physical addresses. It has rotating panels: households residing at the addresses selected to the sample are interviewed for four months, then they are interviewed for additional four months after leaving the sample for eight months. Each person is interviewed up to eight times. Every month, there are eight groups of respondents identified by the month-in-sample (MIS) of their addresses. Because of the 4-8-4 rotating panel structure, about half of the sample interviewed in March will be interviewed again in the following March: MIS 1-4 will be MIS 5-8 in the interview next March. A two-period longitudinal sample from two consecutive years can be constructed from the March Supplements[3].

The data used in the analysis were collected annually from 1980 to 2010, which includes employment and earnings information from 1979 to 2009. In the following discussion, the calendar year refers to the year for which the labor force information is obtained, and the calendar year of the first of two matched years is used to identify two-year matched observations. So the first set of matched observations are collected in 1980 and 1981, and it is referred to as 1979; and the last set of matched observations are collected in 2009 and 2010, and it is referred to as 2008. Estimation is weighted using the individual supplemental weights from the first of two matched years unless otherwise noted.

From these 31 years of cross-sectional data, 1979-2009, it should be possible to construct 30 two-period longitudinal panels. The CPS is redesigned after each decennial census. The census is used to update the sampling frame for the CPS. The sample collected in March of 1986 is the first March file after the 1980 redesign; and the sample collected in March of 1996 is the first March file after the 1990 redesign. So the March files collected in 1985 and 1995 can't be matched forward. The parameters for 1984-1985 and 1994-1995 transitions can't be estimated, so there are 28 years two-period panels in the sample. Details of matching data are discussed in Appendix B.

An advantage of the matched CPS March files is the large sample size. With about half of the 60,000 households in the matched sample, the sample size is much larger than other widely used longitudinal data such as the National Longitudinal Surveys (NLS). Because each of the eight rotation groups in the CPS is a representative sample of the US population, the matched sample from each year includes individuals from various experience levels. In the NLS, a sample of cohorts close in age are followed for many years. Individuals with the same experience level will not usually be observed more than ten years apart in the NLS sample. Because this paper needs to compare individuals of similar experience levels at different points in time, the CPS is better suited for the analysis.

[3] One issue with using the matched CPS March files is that labor force estimates from the matched sample are likely to be biased. The monthly sample of the CPS is representative of the US population, but the matched sample is unlikely to be representative. The CPS samples physical addresses, and there is no attempt to follow people moving out of the sampled addresses. An issue with the matched cross-sections is non-random attrition. Attrition from the sample is correlated with personal characteristics, which in turn is correlated with the labor market status (Peracchi and Welch (1995)). For example, unemployed workers tend to be more mobile because of their needs for new jobs, and they will not be followed once they move to new addresses outside of the sample. So unemployed workers might be under-represented in the matched sample. This paper makes no attempt to address this issue of attrition.

A disadvantage of using the matched CPS March files is the limited information on employment and earnings transitions. For example, in the matched sample, if a worker is employed in the reference week of March of this year and the reference week of last March, the CPS doesn't contain any information on whether the worker has been working for the same employer, or whether there has been any change in earnings during the year between the two reference weeks. Alternatively, if a worker goes from unemployment last March to employment this March, there is not adequate information to determine whether the current job is his first job after the last unemployment spell. Therefore, in the model the relevant decision period is one year: within-year employment and earnings changes are not considered. The labor market outcomes are defined based on the summary information of labor force status in the previous calendar year.

I define employment as having worked for more than 26 weeks in the previous calendar year. The CPS March Supplements doesn't include information on within-year job and earnings changes, so the length of decision period is one year in the empirical study. Employment status should be a summary of a worker's labor force status over one year. A worker should have a sufficiently strong tie to the workplace to be defined as working. Therefore, a worker is defined as employed for the year if he has worked for more than 26 weeks in that year; otherwise, the worker is defined as nonemployed. The results using alternative thresholds to define employment (39 weeks and 13 weeks) are presented in the simulation section.

The outcome of interest is total annual earnings. The main objective of the paper is to study the effect of economic conditions on earnings. Adjustments in labor supply, such as temporary layoff and reduction in hours, are sometimes used by employers to deal with economic hardships. To incorporate labor supply responses to economic conditions, the outcome is given by the total wage and salary earnings in the previous calendar year[4]. All earnings data are deflated to 2000 dollars. The annual earnings of nonemployed workers are set to zero[5]. To deal with outliers, in the matched sample, an observation is excluded if the worker is employed and his earnings is above the 98 percentile or below 3 percentile of earnings distribution in either of the two years .

The analysis focuses on a sample of males (the case for females is discussed later). The

[4]This outcome is consistent with the model. In the model, workers don't make separate decisions on wage rate and hours of work each year.

[5]About 40% of the nonemployed workers in the sample have positive annual earnings, but the average earnings among nonemployed workers with positive earnings is less than 20% of the employed workers with positive earnings.

sample includes civilians aged between 16 and 60. The matched sample is further restricted to wage earners: workers who are self-employed on the longest job held in a year in either of the two matched years are excluded. Only individuals who are active in the labor market are included in the sample: individuals who haven't spent any week of a year working or looking for work are excluded from the sample.

Five education groups are defined: those who haven't complete high school education, high school graduates, those with some college education but without a college degree, college graduates, and those with postgraduate degrees. Because the CPS doesn't include workers' labor market history, to calculate the years of potential labor market experience, I assume that those with high school diploma or less enter the labor market at age 18; those with some college education enter at age 20; and college graduates enter at age 22. The heterogeneity in postgraduate programs leads to large variation in the age of labor market entry for those with postgraduate degrees. There could be a large bias in calculated potential labor market experience if a single age of labor market entry is imposed on that group. So individuals with postgraduate degrees are excluded from the sample. Three groups are defined based on the years of potential labor market experience: 0-10 years, 11-20 years, and 21 plus years.

Summary statistics of the matched sample are discussed next. Note that the summary statistics of the matched sample refer to the labor market information collected in the first of the two matched years. Figure (1) plots the number of observations in the matched sample by year, education, and experience. Individuals in the sample become more educated over time. The number of high school dropouts and high school dropouts decreases over the sample period; and the number of workers with at least some college education increases over the sample period. The experience profile of the sample also changes over time. The number of workers with 20 years of experience or less decreases over time; and the number of workers with more than 20 years of experience increases over time.

Table (1) gives the employment rate and average annual earnings of employed workers by education and experience over the entire sample period. Standard error of the mean and sample size for each group are also included. As expected, more educated workers and more experienced workers are more likely to be employed; and, among employed workers, more educated workers and more experienced workers have higher earnings on average.

The time series of employment show interesting patterns. Figure (2) plots the fraction of employed workers in the sample by year. The rate of employment drops during the recessions in early 1980s, early 1990s and the most recent recession. The cyclicality of employment in the sample is the strongest for the least educated and least experienced workers. Because the cross-sectional distribution of annual earnings is log normal, so the summary statistics of log annual earnings are presented. Log annual earnings don't show significant cyclical pattern (Figure 3). In the matched sample, except for college graduates, all groups experience a decline in real earnings over the sample period. The implication of this pattern on interpreting the estimates will be discussed in the results section. The cross-sectional distribution of log annual earnings also becomes more dispersed over time (Figure 4).

4 Estimation

The set of model parameters to be estimated are $\delta_{a,t}$, $F^0_{a,t}$, $\lambda^0_{a,t}$, $\lambda^+_{a,t}(w)$, $\lambda^-_{a,t}(w)$, and $F^1_{a,t}$, where a is the experience level and t is the time period. The model is estimated using method of moments (MOM).

The probability of transitioning from employment to nonemployment $\delta_{a,t}$, or the rate of job loss, is estimated by the fraction of employed workers in period t with experience level a who becomes nonemployed in period $t+1$; and the probability of transitioning from nonemployment to employment $\lambda^0_{a,t}$, or the rate of re-employment, is estimated by the fraction of nonemployed workers in period t with experience level a who find jobs in period $t+1$. Let $E_{a,t}$ and $N_{a,t}$ denote the number of employed and nonemployed workers with experience level a in period t, respectively. Let $EN_{a,t}$ denote the number of employed workers with experience level a in period t who are nonemployed in period $t+1$, and let $NE_{a,t}$ denote the number of nonemployed workers with experience level a in period t who are employed in period $t+1$. The moment conditions for the probabilities of job loss and re-employment are

$$\delta_{a,t} = \frac{EN_{a,t}}{E_{a,t}}, \tag{6}$$

$$\lambda^0_{a,t} = \frac{NE_{a,t}}{N_{a,t}}. \tag{7}$$

From the model, a nonemployed worker will always accept offers from the earnings distribution $F^0_{a,t}(w)$ because firms will not make an offer with a lower expected value than nonemployment and the non-employed worker will stay in nonemployment if he rejects the offer. Thus, $\widehat{F^0}_{a,t}(w)$ is estimated by the non-parametric kernel density method using the period $t+1$ earnings of workers who transition from nonemployment to employment between periods t and $t+1$.

The parameters of earnings mobility $\lambda^+_{a,t}(w)$ and $\lambda^-_{a,t}(w)$ are identified from the sample of workers with earnings changes between periods t and $t+1$. Let $E^+_{a,t}(w)$ denote the number of employed workers with earnings w and experience level a in period t who get higher earnings in period $t+1$. $E^-_{a,t}(w)$ is defined similarly as the number of employed workers with earnings w and experience level a in period t who get lower earnings in period $t+1$. $E_{a,t}(w)$ is the total number of employed workers with earnings w and experience level a in period t. Define the rates of earnings increase and decrease as

$$p^+_{a,t}(w) \equiv \frac{dE^+_{a,t}(w)}{dE_{a,t}(w)},$$

$$p^-_{a,t}(w) \equiv \frac{dE^-_{a,t}(w)}{dE_{a,t}(w)}.$$

$p^+_{a,t}(w)$ and $p^-_{a,t}(w)$ give the observed rates of earnings increase and decrease in the data. From the model, the probability of an earnings change depends on the arrival rates of offers. An employed worker in period t with annual earnings w has higher earnings in period $t+1$ if an earnings offer arrives and the offer is greater than his current earnings, or $p^+_{a,t}(w) = \lambda^+_{a,t}(w) \cdot (1 - F^1_{a,t}(w))$. Similarly, the worker has lower earnings in period $t+1$ if an earnings offer arrives and the offer is less than his current earnings, or $p^-_{a,t}(w) = \lambda^-_{a,t}(w) \cdot F^1_{a,t}(w)$. The moment conditions for the arrival rates of higher and lower earnings offers are

$$\lambda^+_{a,t}(w) = \frac{p^+_{a,t}(w)}{1 - F^1_{a,t}(w)}, \tag{8}$$

$$\lambda^-_{a,t}(w) = \frac{p^-_{a,t}(w)}{F^1_{a,t}(w)}. \tag{9}$$

So, the offer arrival rates can be estimated given the observed earnings changes in the data, $p^+_{a,t}(w)$ and $p^-_{a,t}(w)$, and the estimate of $F^1_{a,t}(w)$.

The earnings offer distribution $F^1_{a,t}(w)$ is estimated non-parametrically using the flow-balance equation of employment. The difference between the stock of employed workers with experience level $a+1$ in period $t+1$ who earn less than w and the stock of employed workers with experience level a in period t who earn less than w is defined as

$$\Delta E_{a,t}(w) \equiv E_{a+1,t+1}(w) - E_{a,t}(w).$$

This overall change in the stock of employed workers are from several different sources. The inflow into the stock of employed workers earnings less than w consists of formerly nonemployed workers who find employment paying less than w, i.e. $N_{a,t}\lambda^0_{a,t}F^0_{a,t}(w)$, and formally employed workers earnings more than w who have experienced a wage decline to a level below w, i.e. $\left[\int_w^{\overline{w}^1_{a,t}} \lambda^-_{a,t}(x)dE_{a,t,}(x)\right] F^1_{a,t}(w)$. The outflow consists of formerly employed workers earnings less than w who lose their job, i.e. $E_{a,t}(w)\delta_{a,t}$, and formally employed workers earnings less than w who get a raise to a earnings level above w, i.e. $\left[\int_{\underline{w}^1_t}^{w} \lambda^+_{a,t}(x)dE_{a,t,}(x)\right]\left(1-F^1_{a,t}(w)\right)$. To summarize, the change in the stock of employed workers earning less than w with experience level a in period t who are in experience level $a+1$ in period $t+1$ can be expressed as

$$\begin{aligned}\Delta E_{a,t}(w) \quad = \quad & N_{a,t}\lambda^0_{a,t}F^0_{a,t}(w) \\ & + \left[\int_w^{\overline{w}^1_{a,t}} \lambda^-_{a,t}(x)dE_{a,t}(x)\right] F^1_{a,t}(w) \\ & - E_{a,t}(w)\delta_{a,t} \\ & - \left[\int_{\underline{w}^1_t}^{w} \lambda^+_{a,t}(x)dE_{a,t}(x)\right]\left(1-F^1_{a,t}(w)\right). \end{aligned} \tag{10}$$

Rearrange the equation, then the earnings offer distribution for workers who are employed in two consecutive periods $F_{a,t}(w)$ can be expressed as a function of other model parameters

$$F^1_{a,t}(w) = \frac{\Delta E_{a,t}(w) + E_{a,t}(w)\delta_{a,t} + \int_w^{\overline{w}_{a,t}} \lambda^+_{a,t}(x)dE_{a,t}(x) - \lambda^0_{a,t}N_{a,t}F^0_{a,t}(w)}{\int_w^{\overline{w}_{a,t}} \lambda^-_{a,t}(x)dE_{a,t}(x) + \int_{\underline{w}_{a,t}}^{w} \lambda^+_{a,t}(x)dE_{a,t}(x)}. \tag{11}$$

Conditional on the estimates of the transition rates, $\delta_{a,t}$, $\lambda^0_{a,t}$, $\lambda^+_{a,t}(w)$, and $\lambda^-_{a,t}(w)$, and the offer distribution for newly employed workers $F^0_{a,t}(w)$, the earnings offer distribution $F^1_{a,t}(w)$ can be estimated non-parametrically given the earnings data of the two periods.

To summarize, the model is estimated using the MOM. The rates of job loss and re-employment can be estimated from the moment conditions in Equations (6) and (7), respectively.

The earnings offer distribution of newly employed workers are estimated non-parametrically from the earnings of workers who becomes employed in period $t+1$ after nonemployment in period t. Given the estimates of the rates of job loss and re-employment, $\delta_{a,t}$ and $\lambda^0_{a,t}$, and the earnings offer distribution for newly employed workers $F^0_{a,t}(w)$, the set of equations (8), (9) and (11) is a fixed-point equation system of the arrival rates of offers $\lambda^+_{a,t}(w)$ and $\lambda^-_{a,t}(w)$ and the offer distribution $F^1_{a,t}(w)$. The arrival rates and the offer distribution can be estimated by iterating between the three equations until convergence.

BR also mentions alternative choices for expectations, such as rational expectation and adaptive expectation. Given the behavioral model presented above, no earnings offer is ever rejected, so the earnings dynamics are completely governed by the model parameters estimated from the current period sample. From the estimation procedure, it is clear that the assumption of a specific form of expectation affects the present value of labor market status, but not the identification of model parameters. The choice of expectations in the model will not affect the simulation results[6].

To simplify estimation, model parameters are constrained to be constant within each education-experience group. So the set of model parameters in period t are $\{\delta_{i,j,t}, F^0_{i,j,t}, \lambda^0_{i,j,t}, \lambda^+_{i,j,t}, \lambda^-_{i,j,t}, F^1_{i,j,t}\}$ where $i \in \{1,2,3\}$ indicates one of the three experience groups and $j \in \{1,2,3,4\}$ indicates one of the four education groups defined in the sample. Details of implementing the estimation are given in Appendix C.

The approach of this paper departs from the reduced-form analysis of business cycle and earnings dynamics. The reduced-form studies use the economy-wide unemployment rates to measure general labor market conditions without further discussing the channel through which the aggregate unemployment rates affect individual labor market outcomes. In this paper, I make explicit that the business cycle affects earnings through its contemporaneous interaction with employment and earnings mobility[7]. Using this non-stationary model, I can estimate the actual labor

[6] If the model allows a certain channel through which the expectations about future labor market conditions affect the current period mobility decision, then the search friction parameters of the model can't be identified from the employment status and earning transitions over two periods. In this case, both the parameters of search friction and the parameters governing the expectation formation process jointly determine wage growth. We need additional information to identify the parameters of expectation formation (see Buchinsky and Leslie (2010) for an example of identification of adaptive expectation in the context of dynamic choice model).

[7] The assumption is likely to be violated if economic conditions affect education choice (Clark (2009) and Card and Lemieux (2002)), they have long-term effect on beliefs (Giuliano and Spilimbergo (2009)), or economic conditions at job displacement signal a worker's quality his current and future employers (Nakamura (2008)).

market transitions for each year in the sample period. Because the parameters estimated from the sample of a year reflect the economic conditions of that year, earnings trajectories under different economic conditions can be simulated by using parameters of different years to determine employment and earnings transitions. The lifecycle effect of adverse economic conditions on expected lifetime earnings can be estimated by imposing parameters estimated using sample of different years at different points of a career and comparing the outcomes of those earnings trajectories.

5 Results

5.1 Estimates of Model Parameters

In the model, employment and earnings transitions are governed by the set of model parameters. Whether the effect of economic conditions on earnings varies by experience level depends on how the time series of model parameters vary over time and across experience groups. Before presenting the simulation results, time series of the estimated model parameters are presented. All the parameters are presented by year and education group, or by year and experience group.

I first present the parameters of employment mobility estimated from the matched CPS March files. Figure (5) plots the estimated probabilities of an employed worker becoming nonemployed next year, or the rates of job-loss. The rate of job-loss is higher for less educated and less experienced workers, which are the groups least expected to have stable job matches. The rates of job-loss show greater variability over the sample period for less educated and less experienced workers. There are also several visible peaks in the job-loss rates, which coincide with the period of economic recessions. The height of those peaks also seems to relate to the severity of recessions: the highest peak in the rate of job-loss occurs around the most recent recession that started in 2008, and the second highest peak in the sample occurs around the early 1980s recession. There are also visible peaks around the early 1990s and the early 2000s recessions. Overall, the estimated rates of job-loss by education and experience are consistent with the business cycle fluctuations, and the cyclical variation is stronger for less educated and less experienced workers[8].

Contrary to this assumption, Frühwirth-Schnatter, et al. (2011) estimate a stationary Markov chain with clustering that depends on observable characteristics. The assumption is that transition parameters are stationary over a career and their values depend on the economic conditions at labor market entry.

[8] Figure (D.2) includes bootstrapped 90% confidence intervals for the estimates by year for each education and experience group. The differences between the peaks and the troughs of the estimates over time are generally

Figure (6) plots the estimated probabilities of transitioning from nonemployment to employment, or the rates of re-employment. Less educated workers have lower rates of re-employment. The rates are similar across experience groups. The estimates are noisy[9]. This is due to the small proportion of nonemployed workers in the sample: only about 10% of the sample are nonemployed in any given year. There doesn't seem to be any robust trend or pattern in the rates of re-employment along the time dimension[10].

For workers who are employed for two consecutive years, the means and standard deviations of estimated offer distributions of log annual earnings are plotted in Figures (7) and (8), respectively. More educated and more experienced workers face earnings offer distributions with higher means. Except for the group of college graduates, the means of the offer distributions decreases over time. There does seem to be cyclical trend in means of the offer distributions for the least educated and the least experienced workers: for workers with less than high school education and experience level 10 years of less, means of the offer distributions drop in early 1980s, early 1990s and 2008[11].

The parameters of earnings increase show cyclical pattern. Figure (9) plots the predicted probabilities of earnings increase, or $\widehat{p}^{+} = \widehat{\lambda^{+}} \cdot \int_{\underline{w}^1}^{\overline{w}^1} \left(1 - \widehat{F^1}(w)\right) d\widehat{G}(w)$. The predicted probabilities of earnings increase vary with worker characteristics and economic conditions. They are lower for less educated and more experience workers. The probabilities of earnings increase are low when the macroeconomic conditions are bad, for example, during the recessions in early 1980s, early 1990s, early 2000s, and 2008[12].

statistically significant for lower-educated and less-experienced workers. For more experienced workers with college degrees, the variation is usually not statistically significant.

[9] See Figure (D.3) for bootstrapped 90% confidence intervals.

[10] Previous studies have shown that aggregate measures of worker flows are cyclical (Blanchard and Diamond (1990) and Davis and Haltiwanger (1999)). However, the estimates in this study is not directly comparable with those earlier studies on cyclicality of worker flows. Those studies use higher-frequency data series to look at the change in status between two points in time that are one month apart. The estimates here are based on a summary statistic of employment status over a year (a worker is defined as employed if having worked more than 26 weeks in a year), and they measure the probability of status change between two consecutive years. Many episodes of job changes are not captured by the estimated transition rates in this paper.

[11] Bootstrapped 90% confidence intervals for means of the earnings offer distributions are given in Figures (D.4). For each education-experience group, variation in the means of the earnings offer distributions over time is statistically significant.

[12] Figure (D.5) plots the predicted probabilities of earnings increase by year, experience, and education with 90% bootstrapped confidence intervals. Variation over time is generally not statistically significant. The confidence intervals are large except for workers in the lowest experience group. For less experience workers, the observed rate of earnings increase are high, and the arrival rates of a higher earnings offer don't vary too much. This is due to the restriction imposed in the estimation procedure. For each year and education-experience group, sum of the arrival rate of a higher earnings offer and the rate of job-loss is constrained to be less than 1 (see Appendix C for details). When the observed rate of earnings increase is high, the constraint becomes binding. So the confidence intervals of the predicted probabilities of earnings increase are small for less experience workers who have higher observed rates

Figure (9) plots the predicted probabilities of earnings decrease, or $\widehat{p^-} = \widehat{\lambda^-} \cdot \int_{\underline{w}^1}^{\overline{w}^1} \widehat{F^1}(w) d\widehat{G}(w)$. The pattern contrasts with the pattern of the parameters of earnings increase. They are higher for more experience workers. The data series are noisy, especially after the 1994 CPS redesign[13].

In summary, the estimated model parameters exhibit cyclicality. During the period of recessions, employed workers are likely to become nonemployed; and for those who remain employed, they are less likely to receive a higher earnings offer. This pattern over time is consistent across experience groups. In addition, more experienced workers tend to have lower rates of both employment and earnings mobility. If a cohort of workers experience a slower rate of earnings growth early in their careers, they might not be able to catch up with other cohorts easily because there are less opportunities for an earnings increase later in career. This could lead to a persistent effect of labor market conditions early in career on earnings. The values of the estimated parameters also vary with education level: less educated workers face a higher rate of job-loss and a lower rate of earnings increase. The overall effect of economic conditions on expected lifetime earnings might be different among workers of different education levels.

5.2 Parameter Estimates and Aggregate Measure of Economic Conditions

In this paper, the lifecycle effect of economic conditions on expected lifetime earnings is identified by variation of the model parameters over time and experience level. In the estimation, no restriction has been imposed on the movement of model parameters over time. To see whether the estimated model parameters relate to the actual business cycle fluctuations, the model parameters are compared with aggregate measures of macroeconomic conditions, for example, national unemployment rate for men published by the Bureau of Labor Statistics (BLS) (Figure 11).

The reason for this exercise is two-fold. First, I want to connect my study with the previous reduced-form studies of economic conditions and earnings that use the economy-wide unemployment rates to identify economic conditions. This study is consistent with those previous estimates if the business cycle induces the same movement in the aggregate unemployment rates and measures of economic conditions based on the estimated model parameters in this paper. Theoretically, this consistency is guaranteed. Based on the model, there is a deterministic relationship between the

of earnings increase.

[13] Variation over time is not statistically significant (Figure D.6).

rate of nonemployment, the change in nonemployment rate, and model parameters:

$$\Delta u_{i,j,t} = (1 - u_{i,j,t}) \cdot \delta_{i,j,t} + u_{i,j,t} \cdot \lambda^0_{i,j,t},$$

where $u_{i,j,t}$ and $\Delta u_{i,j,t}$ are the proportion of nonemployed workers and the annual change of that proportion in the sample of the matched CPS March files, respectively. The unemployment in the BLS estimates and the nonemployment defined in this paper are two related but different concepts. The BLS unemployment rates are estimated from the monthly CPS sample. That is a different sample from the matched CPS March files because of attrition over time. In addition, the definition of unemployment in the BLS estimates is based on the labor force status during one week of a month, and nonemployment in this paper is defined as a summary statistic of labor force status over a year. For the above reasons, the official unemployment rates released by the BLS will be different from the estimated rates of nonemployment in this paper. But the two measures should be closely related because they both measure size of the US workforce. If other model parameters are incorporated to the measure of economic conditions, the correlation between the measure of economic conditions based on the estimated model parameters and the BLS estimates of unemployment rates is not guaranteed. It is therefore informative to look at the relationship between these two measures of economic conditions.

Secondly, this exercise serves as an indirect test on the validity of empirical strategy used in this paper. The identification assumption of this paper is that the business cycle induces fluctuations in labor market transitions, and the model is sufficient for capturing variation in economic conditions over time. Spurious trend in the measure of economic conditions based on the estimated model parameters would cast doubt on the results and their interpretation.

Instead of looking at each parameter separately, a measure of economic conditions is generated from all four transition parameters and two wage offer distributions. There are 31 years of the CPS March Supplements, therefore 28 sets of estimated transition parameters and earnings offer distributions for each of the three experience groups and four education groups[14]. Given a set of estimated model parameters for a year and a education group, a 35-year earnings profile is

[14] Recall that the March files collected in 1985 and 1995 can't be matched forward due to changes in sampling frame. Because the parameters are estimated from two-year panel data, N years of matched data will yield (N-1) sets of parameters.

simulated using those parameters values, i.e. that same set of model parameters govern a worker's labor market transitions for 35 years; and as the worker's labor market experience increases, the parameters corresponding to the relevant experience group are used to simulate employment and earnings transitions. For each year and education group, 2,000 earnings trajectories are simulated. For each simulation, annuity value of the discounted total lifetime earnings at 5% interest rate is defined a measure of labor market strength. The formula for annuity of value V is

$$\frac{V}{\sum_{t=0}^{A-1-a} \frac{1}{(1+r)^t}} = rV \frac{(1+r)^{A-1-a}}{(1+r)^{A-a} - 1}.$$

The measure of economic conditions is defined as the average annuity value from these 2,000 simulations. Panel (a) of Figure (12) plots the measure averaged over the four education groups. Panel (a) of Figure (13) looks at the relationship between this measure of economic conditions and the proportional change in the annual unemployment rates for men. The measure of economic conditions based on the model parameters is negatively correlated with the annual change in unemployment rates: the correlation coefficient is -0.71. So the estimated model parameters are consistent with economic conditions as measured by the national unemployment rates for men.

An alternative measure of economic conditions based on the estimated model parameters is ex-ante welfare. The ex-ante welfare for a worker is the expected value of his current labor market status under static expectations. For a nonemployed workers of experience level a and education group j in period t, the ex-ante welfare is $V_{a,j,t}$; and for an employed worker earnings w of experience level a and education group j in year t, the ex-ante welfare is $W_{a,j,t}(w)$. To compare workers with different years of experience, the annuity of ex-ante welfare with 5% interest rate is calculated for each worker in the sample. The average ex-ante welfare of workers in a year is used as a measure of economic conditions for that year. Panel (b) of Figure (12) plots the average ex-ante welfare over time, and Panel (b) of Figure (13) looks at its relationship with the proportional changes in annual unemployment rates. The correlation coefficient between the average ex-ante welfare and the proportional change in annual unemployment rates is -0.44.

Both measures of economic conditions based on the estimated model parameters are correlated with the change in economy-wide unemployment rates. This result offers some support for using the model to study the effect of economic conditions on earnings. These two measures will guide the ranking of years by economic conditions in the next section.

5.3 Simulations

The estimated model parameters exhibit cyclical pattern, and their variation over time is correlated with economic conditions as measured by the economy-wide unemployment rates. Next, I use these estimated model parameters to study how much the timing of economic conditions matters expected lifetime earnings.

In the non-stationary model of job search, the parameters of employment and earnings mobility for each year (and education-experience group) are estimated independently using the sample from that year (and that education-experience group). Change in economic conditions is identified by variation of estimated model parameters. Under this identification assumption, a worker is said to experience economic conditions of a year if his employment and earnings transitions to the next year are determined by the set of model parameters estimated from the sample of that year.

The identification assumption implies absence of time trend in labor market status. This is a standard issue of separating the year effect and the cohort effect in longitudinal data, and the identification assumption of this paper translates into no cohort effect. As mentioned in the data section, except for the college graduates, the average real annual earnings of male workers in the sample show a steady decline over the sample period[15]. This feature the sample invalidates the assumption of no cohort effect. The implications of this issue will be discussed later in this section. For now, the simulation results are interpreted under the assumption that change in economic conditions can be identified by variation of the model parameters over time.

In the simulation, each worker remains in the labor market for 35 years. A worker could experience adverse economic conditions at different points of his career. Three cases are considered. In each case, a worker experiences the "average" economic conditions except for a 5-year experience of the "adverse" economic conditions at one point in his career. In different cases, the "adverse" economic conditions occur at different points of the career: at labor market entry, after 10 years of experience, or after 20 years of experience. Average of the two measures of economic conditions discussed in the previous section has the lowest value in 2008. A worker is therefore said to

[15] The magnitude of this decline in average earnings is not insignificant (Figure D.1).

experience the "adverse" economic conditions for a year if his employment and earnings transitions are governed by the model parameters estimated from the matched 2009-2010 sample.

The outcome of interest is the expected lifetime earnings. The lifecycle effect of adverse economic conditions on earnings is estimated by comparing the outcomes of workers who experience the adverse economic conditions at various points of their careers with the baseline scenario. At the baseline, a worker experiences the "average" economic conditions through his entire career.

The study of lifecycle effect of adverse economic conditions on earnings is complemented by additional simulations that estimate the lifecycle effect of positive economic shocks on earnings. The three cases of positive economic shocks during the career are defined similarly as for the simulated effect of adverse economic shocks. Workers experience the "average" economic conditions except for a 5-year experience of the "positive" economic conditions. And three groups of workers experience the "positive" economic shocks at different experience levels: labor market entry, 11 years of experience, or 21 years of experience. The two measures of economic conditions based on the estimated model parameters suggest that the economic conditions in 1997-1999 are the best during the sample period. So a worker is defined as experiencing the "positive" economic conditions for a year if his employment and earnings transitions are governed by the average model parameters from 1997-1999.

Given years of the "adverse" and positive" economic conditions, a worker is said to experience the "average" economic conditions if his employment and earnings transitions are determined by the average parameter values during sample period except for 1997-1999 and 2008.

Not only do I want to quantify the lifecycle effect of economic conditions on expected lifetime earnings, I also want to estimate how much the variation of each model parameter over time contributes to the overall effect. To formalize this idea, I decompose the (negative) effect of adverse economic conditions on expected lifetime earnings into two components: employment and earnings. Out of the five estimated model parameters that vary with time, $\{\delta, \lambda^0, \lambda^+, \lambda^-, F^1\}$, δ and λ^0 determine the transitions in and out of employment, and λ^+, λ^-, and F^1 jointly determine the earnings changes for employed workers. To study the lifecycle effect of employment mobility on earnings, earnings profiles are simulated for three cases of adverse economic conditions using the earnings parameters of the average economic conditions for the entire career; and to study the lifecycle effect of earnings mobility, the employment parameters of the average economic conditions are used in the simulations.

Table (2) presents the values of transition parameters and means of the earnings offer distributions used in the simulations. For each education and experience group, the parameters under the average economic condition are followed by the parameters from 2008, or the year with the adverse economic conditions, and average of the parameters from 1997-1999, or the years with the positive economic condition[16]. I would expect that, comparing to the average economic conditions, the adverse economic conditions lead to higher job-loss rates, lower re-employment rates, lower arrival rates of a higher earnings offer, higher arrival rates of a lower earnings offer, and an earnings offer distribution with a higher mean. The opposite is expected for the parameters under the positive economic conditions. In most cases, the parameter values conform with the expectations. There are cases of exception for the arrival rates of a lower earnings offer; and means of the earnings offer distributions under different economic conditions don't conform to the expectations for more educated workers. In addition, means of earnings offer distributions for newly employment workers $F^0_{a,t}$ are always lower than those for workers who have been continuously employed for two years $F^1_{a,t}$, and the difference increases with experience. So a spell of nonemployment worsens workers' standings in the labor market.

The results of adverse economic conditions is presented first. For each of the four education groups, given earnings 0 in year 0, 35-year earnings trajectories are simulated for the baseline group and three groups who experience adverse economic shocks at different experience levels. The outcome of interest is the annuity value of discounted lifetime earnings with 5% interest rate. Comparing the outcome of each of the three groups with the baseline group will answer the question of how much the timing of adverse economic conditions matters for expected lifetime earnings.

The estimated lifecycle effect of adverse economic conditions on annuity of lifetime earnings and the decomposition results are presented in Table (3). For each scenario, 2,000 earnings profiles are simulated. Both the annuity of discounted lifetime earnings averaged over 2,000 simulations and standard errors of the average (in parentheses) are included in the table. Compare to the baseline case (Column 1), adverse economic conditions are the most damaging to a worker's expected lifetime

[16]The earning offer distributions for workers who transition from nonemployment to employment, $F^0_{a,t}$, are estimated for each education-experience group using the full sample over the entire sample period (see Appendix C for details). So the same earning distribution is used to simulate transitions under the average, the worst, and the best economic conditions.

earnings if they occur early in his career. This is true for workers of all education levels[17]. For workers with less than high school education, the experience of adverse economic conditions at labor market entry lowers their expected lifetime earnings by 5.84%; if the adverse economic conditions occur after 20 years of labor market experience, the effect on their expected lifetime earnings is only -3.33%. For high school graduates, the effects of adverse economic conditions at labor market entry and after 20 years of experience are -6.26% and -2.52%, respectively. Magnitude of the negative effects decreases with education. For workers with some college education, adverse economic conditions at labor market entry lower their expected lifetime earnings by 1.90%; and the effect is -2.78% for college graduates.

The decomposition results in Table (3) suggest that employment mobility is a more important factor than earnings mobility in explaining the negative effect of adverse economic conditions on expected lifetime earnings. For workers with less than high school education, the negative effect of adverse economic conditions on expected lifetime earnings is -5.84%. The effect of employment mobility (δ and λ^0) on the expected lifetime earnings is -4.90%; and the effect of earnings mobility (λ^+, λ^-, and F^1) is only -1.30%. This is true for all cases where adverse economic conditions lead to a significant decline in expected lifetime earnings[18]. The evidence here is consistent with earlier works on mobility and earnings growth, such as Neumark (2002). He finds that excessive job mobility early in career as predicted by local unemployment rate is harmful for earnings growth.

The effect of positive economic shocks on lifetime earnings should mirror the results of adverse economic shocks. Table (4) presents the simulation results. Though magnitude of the effect differs from the case of adverse economic conditions, the main conclusion holds true in the case of positive economic conditions. Experience of the positive economic conditions is the most beneficial for young workers. For those with less than high school education and some college education, experience of the positive economic conditions for 5 years at labor market entry increases expected lifetime earnings by about 3%; experience of the positive economic conditions for 5 years after 20

[17] For workers with some college education, magnitude of the estimated negative effect is actually lower if they at labor market entry than after 10 years in the labor market, or 1.90% versus 2.48%. But the difference is not statistically significant.

[18] Simulations based on samples with alternative definitions of employment yield the same conclusion (Table D.1). A worker is defined as employed for a year if he has worked for more than 26 weeks in that year. In the alternative definitions of employment, the cutoff is either 39 or 13 weeks. The conclusion from the main text holds for these samples with different definitions of employment: experience of adverse economic conditions early in career has a greater negative effect on lifetime earnings, and magnitude of the negative effect decreases with education. Parameters of employment mobility explain most of the negative effect.

years of experience yields no benefit. As in the case of adverse economic conditions, most of the benefit from the positive economic conditions is due to the parameters of employment mobility. However, contrary to the large negative effect of adverse economic conditions on expected lifetime earnings for high school graduates, positive economic conditions yield no benefit for the group[19]. And it is not clear that the benefit of positive economic conditions decreases with education.

Recall that the real earnings decrease over the sample period, and this feature of the sample violates the identification assumption that variation of model parameters reflect change in economic conditions. Violation of the assumption will introduce bias in the estimated lifecycle effect of economic conditions on expected lifetime earnings since not all the variation in model parameters can be explained by change in economic conditions. The decomposition results make this issue less worrisome. The adverse economic conditions are defined by the estimated parameters of 2008. Given the declining trend in average real earnings, the severity of adverse economic condition in 2008 is overstated, and the overall negative effect of adverse economic conditions on expected lifetime earnings is overstated as well. But since variation in parameters of earnings mobility is not very important for explaining the overall effect, the bias in the overall effect should be small as well. A similar argument follows for the estimated lifecycle effect of the positive economic conditions on expected lifetime earnings: since the parameters of earnings mobility play a small role in explaining the overall positive effect, the bias in the overall effect due to the secular trend in annual earnings should be small as well. Though the identification assumption is violated, I conjecture that the main conclusion will not change even after accounting for the bias.

Because of the issue with the identification assumption, it is not straightforward to extend the study to female workers. A sample of female workers is obtained from the matched CPS March Supplements. The sample of female workers is constructed in the same way as the sample of male workers used in this paper. For this sample of female workers, there is a steady and large increase in both the rate of employment (Figure 14) and the real annual earnings (Figure 15) over the sample period. This time trend in labor force status will lead to time trend in estimated model parameters. This is indeed the case. If the non-stationary search model is estimated using the sample of female workers, both measures of economic conditions as defined in the previous section (simulated 35-year earnings profile and average ex-ante welfare) increase during the sample period

[19] Simulations based on samples with alternative definitions of employment yield the same conclusion (Table D.2).

(Figure 16). The assumption of no cohort effect is clearly violated for the sample of female workers, so the framework in this study can't be applied directly to estimate the lifecycle effect of economic conditions on expected lifetime earnings for female workers. The key to solving this problem is to identify the year effect and the cohort effect separately. This can be achieved by incorporating the time trend of labor force characteristics of female workers into the model. The extension is beyond the scope of this paper. This paper focuses on the sample of male worker in the matched CPS March Supplements.

6 Conclusion

This paper studies whether the effect of economic conditions on earnings varies by experience level. More specifically, I estimate how much the sequence of economic conditions over a worker's career matters for his expected lifetime earnings. The theory of job search and specific human capital suggest persistent and large earnings losses under adverse economic conditions for both young and experienced workers. Past empirical studies on economic conditions and earnings have focused on workers from a particular age group. So those studies are unable to provide an answer to the question.

To capture the interaction between economic conditions and earnings growth, I estimate a discrete-time non-stationary job search model. The change in economic conditions is identified by the variation of estimated model parameters. The model is estimated using MOM, and the variation of estimated parameters over time is correlated with the annual unemployment rates for men estimated by the BLS. Simulations based on the estimated parameters show that experience of the adverse economic conditions early in career has the greatest negative effect on expected lifetime earnings. For workers with high school degrees and lower, experiencing the worst economic conditions of the sample period (defined as 2008) for 5 years at labor market entry lowers their expected lifetime earnings by around 6%. If they experience the conditions of 2008 for 5 years after 20 years in the labor market, their lifetime earnings decline by around 3%. Magnitude of the negative effect decreases with education. Decomposition of the overall effect indicates that variation in the parameters of employment mobility over time (transitions between employment and nonemployment) is more important in explaining this negative effect than variation in the parameters of earnings mobility over time. The estimated lifecycle effect of positive economic conditions mirrors the results for adverse economic conditions.

However, the results should be interpreted with caution. The assumption of this study is that variation of the model parameters over time identifies change in the economic conditions. Because real annual earnings decline over the sample period, variation of the model parameters captures more than just change in the economic conditions. This will introduce bias in the estimated lifecycle effect of economic conditions on earnings. Decomposition results suggest that this bias is likely to be small. The conclusion from this paper will likely to hold even after accounting for this bias.

The evidence suggests potential benefits in assisting young workers during economic downturn, especially for less educated workers. Decomposition results point to the important role of employment instability in explaining the negative effect of adverse economic conditions on lifetime earnings. Active labor market policies that help young workers build a stable career would have long-term positive effect on earnings by reducing excessive instability in job matches during recessions.

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Table 1: Summary statistics of the sample.

	Experience (years)					
	Employment rate			Average annual earnings of employed workers		
	0-10	11-20	21+	0-10	11-20	21+
A. Less than HS						
Mean	0.661	0.845	0.867	20,505	25,857	29,705
SE	0.005	0.004	0.002	152	154	112
N	7,545	8,035	19,309	5,120	6,905	16,781
B. HS graduates						
Mean	0.809	0.922	0.917	24,715	33,867	37,741
SE	0.002	0.002	0.001	88	96	82
N	24,802	26,695	44,723	20,206	24,754	41,232
C. Some college						
Mean	0.801	0.939	0.926	28,748	40,288	43,767
SE	0.003	0.002	0.002	123	133	126
N	18,152	18,037	25,207	14,728	16,990	23,396
D. College graduates						
Mean	0.910	0.963	0.937	39,390	50,603	53,348
SE	0.002	0.002	0.002	163	190	196
N	13,212	12,754	14,419	12,131	12,316	13,586

Note: The summary statistics are based on the sample over the entire sample period, 1980-2010. Employment rate is the proportion of employed workers in the sample, and the annual earnings are deflated to 2000 dollar. Summary statistics (mean, standard error, and number of observations) for these two variables are presented by education and experience.

Table 2: Values of estimated parameters used in the simulations by education and experience.

Education	Experience (years)								
	1-10			11-20			21+		
	Average	Worst	Best	Average	Worst	Best	Average	Worst	Best
A. Less than HS									
δ	0.14	0.27	0.15	0.09	0.07	0.08	0.10	0.17	0.09
λ^0	0.34	0.27	0.43	0.42	0.41	0.48	0.42	0.24	0.44
λ^+	0.83	0.73	0.83	0.86	0.71	0.89	0.79	0.83	0.91
λ^-	0.72	0.51	0.81	0.79	0.93	0.85	0.84	0.64	0.77
Mean of log F^1	9.50	8.74	9.60	9.85	9.75	9.90	10.07	9.85	9.98
SD of log F^1	0.60	0.99	0.55	0.55	0.62	0.53	0.53	0.52	0.52
Mean of log F^0	9.39			9.57			9.60		
SD of log F^0	0.51			0.51			0.61		
B. HS graduates									
δ	0.09	0.19	0.08	0.05	0.14	0.04	0.06	0.13	0.05
λ^0	0.46	0.30	0.47	0.50	0.50	0.54	0.42	0.30	0.50
λ^+	0.90	0.81	0.92	0.92	0.69	0.95	0.86	0.69	0.87
λ^-	0.71	0.69	0.73	0.79	0.86	0.82	0.84	0.85	0.90
Mean of log F^1	9.79	9.58	9.90	10.24	10.16	10.25	10.40	10.40	10.40
SD of log F^1	0.54	0.64	0.50	0.49	0.53	0.49	0.48	0.50	0.49
Mean of log F^0	9.55			9.80			9.86		
SD of log F^0	0.51			0.58			0.63		
C. Some college									
δ	0.07	0.15	0.05	0.04	0.08	0.04	0.06	0.09	0.05
λ^0	0.38	0.38	0.45	0.53	0.30	0.59	0.43	0.33	0.46
λ^+	0.92	0.85	0.95	0.92	0.78	0.96	0.85	0.76	0.95
λ^-	0.68	0.69	0.67	0.79	0.90	0.78	0.82	0.83	0.80
Mean of log F^1	9.85	9.76	9.99	10.43	10.44	10.40	10.53	10.49	10.51
SD of log F^1	0.61	0.61	0.56	0.48	0.53	0.51	0.49	0.53	0.49
Mean of log F^0	9.46			9.75			9.88		
SD of log F^0	0.64			0.68			0.67		
D. College graduates									
δ	0.03	0.07	0.02	0.02	0.07	0.02	0.05	0.07	0.04
λ^0	0.64	0.50	0.55	0.61	0.33	0.77	0.42	0.15	0.44
λ^+	0.97	0.93	0.98	0.96	0.74	0.98	0.89	0.82	0.92
λ^-	0.63	0.60	0.64	0.70	0.83	0.70	0.76	0.74	0.81
Mean of log F^1	10.31	10.21	10.37	10.59	10.75	10.64	10.65	10.65	10.69
SD of log F^1	0.52	0.60	0.57	0.51	0.50	0.53	0.52	0.57	0.52
Mean of log F^0	9.88			10.12			9.96		
SD of log F^0	0.59			0.66			0.83		

Note: The "average" parameters are the averages of model parameters from the entire sample period except for the years with "adverse" or "positive" economic conditions. The "adverse" parameters are the averages of model parameters from the years with the worst economic conditions during the sample period (2008 in this case), and the "positive" parameters are the averages of model parameters from the years with the best economic conditions during the sample period (1997-1999 in this case).

Table 3: Decomposition of the lifecycle effect of adverse economic conditions on lifetime earnings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		5-Year Adverse Economic Shocks					
		Years 1-5		Years 11-15		Years 21-25	
	Baseline	Level	% Δ	Level	% Δ	Level	% Δ
A. Less than HS							
All	16,164	15,219	-5.84	16,130	-0.21	15,625	-3.33
	(88)	(82)		(85)		(87)	
δ, λ^0		15,371	-4.90	16,393	1.42	15,811	-2.18
		(84)		(86)		(88)	
$\lambda^+, \lambda^-, F^1$		15,954	-1.30	16,017	-0.91	16,024	-0.87
		(84)		(85)		(85)	
B. HS graduates							
All	23,324	21,865	-6.26	22,237	-4.66	22,737	-2.52
	(97)	(95)		(96)		(98)	
δ, λ^0		21,919	-6.03	22,720	-2.59	22,926	-1.70
		(95)		(97)		(98)	
$\lambda^+, \lambda^-, F^1$		23,150	-0.75	22,764	-2.40	23,155	-0.73
		(96)		(94)		(96)	
C. Some college							
All	27,257	26,739	-1.90	26,580	-2.48	26,869	-1.42
	(113)	(111)		(118)		(114)	
δ, λ^0		26,880	-1.38	26,663	-2.18	27,020	-0.87
		(112)		(117)		(114)	
$\lambda^+, \lambda^-, F^1$		27,033	-0.82	27,225	-0.12	27,127	-0.48
		(111)		(113)		(112)	
D. College graduates							
All	38,946	37,863	-2.78	38,132	-2.09	38,614	-0.85
	(119)	(127)		(129)		(122)	
δ, λ^0		37,680	-3.25	38,093	-2.19	38,483	-1.19
		(123)		(126)		(121)	
$\lambda^+, \lambda^-, F^1$		39,033	0.22	38,932	-0.04	39,069	0.32
		(123)		(121)		(119)	

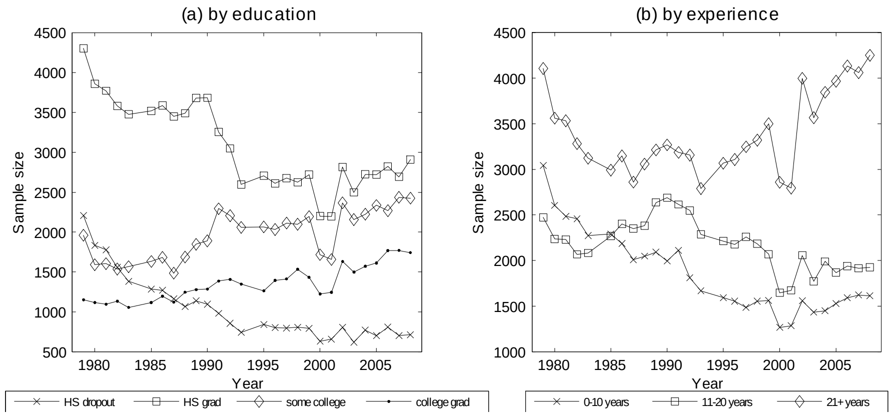
Note: Annuity of discounted lifetime earnings presented in the table is the average of 2,000 simulations. Standard errors of the averages are given in the parentheses. At the baseline, the labor market transitions are determined by the average of estimated parameters over the sample period, 1979-2008 (except for the years with adverse or positive economic conditions, or 1997-1999 and 2008). A worker is said to experience adverse economic shocks if his labor market transitions are determined by the set of parameters from the years with adverse economic conditions (2008 in this case). Three cases of adverse labor market shocks are simulated by imposing a 5-year experience of adverse economic conditions at different points of the worker's career: at labor market entry, after 10 years in the labor market, and after 20 years in the labor market. The overall effect of adverse economic conditions on earnings is decomposed into two components: employment (δ, λ^0) and earnings$(\lambda^+, \lambda^-, F^1)$. The estimates are obtained by fixing either the parameters of employment or the parameters of earnings at the average levels during adverse economic shocks.

Table 4: Decomposition of the lifecycle effect of positive economic conditions on lifetime earnings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		5-Year Positive Economic Shocks					
		Years 1-5		Years 11-15		Years 21-25	
	Baseline	Level	% Δ	Level	% Δ	Level	% Δ
A. Less than HS							
All	16,164	16,686	3.23	16,462	1.84	16,245	0.50
	(88)	(85)		(85)		(86)	
δ, λ^0		16,666	3.11	16,418	1.58	16,295	0.81
		(86)		(85)		(86)	
$\lambda^+, \lambda^-, F^1$		16,252	0.54	16,309	0.90	16,180	0.10
		(86)		(85)		(86)	
B. HS graduates							
All	23,324	23,525	0.86	23,531	0.89	23,398	0.32
	(97)	(96)		(94)		(95)	
δ, λ^0		23,441	0.50	23,507	0.78	23,412	0.38
		(96)		(94)		(95)	
$\lambda^+, \lambda^-, F^1$		23,408	0.36	23,378	0.23	23,333	0.04
		(97)		(95)		(96)	
C. Some college							
All	27,257	28,096	3.08	27,496	0.88	27,383	0.46
	(113)	(112)		(111)		(112)	
δ, λ^0		27,888	2.32	27,379	0.45	27,371	0.42
		(110)		(110)		(112)	
$\lambda^+, \lambda^-, F^1$		27,439	0.67	27,439	0.67	27,292	0.13
		(115)		(112)		(112)	
D. College graduates							
All	38,946	38,966	0.05	39,610	1.71	39,171	0.58
	(119)	(126)		(118)		(118)	
δ, λ^0		38,376	-1.46	39,100	0.40	39,054	0.28
		(120)		(116)		(117)	
$\lambda^+, \lambda^-, F^1$		39,512	1.45	39,435	1.26	39,066	0.31
		(125)		(120)		(118)	

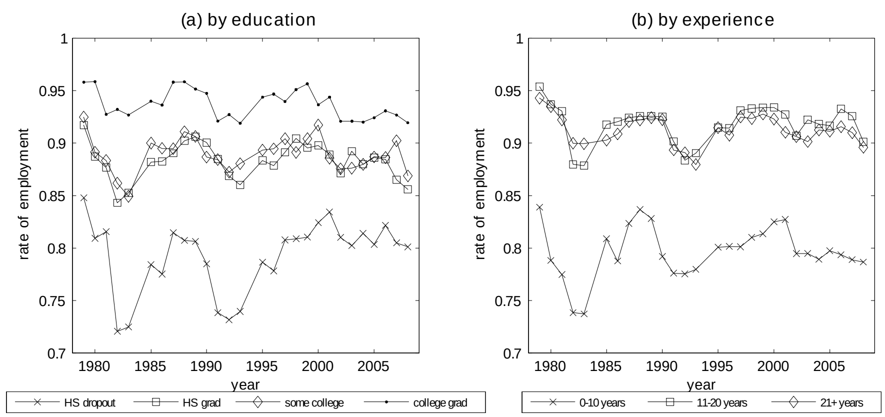
Note: Annuity of discounted lifetime earnings presented in the table is the average of 2,000 simulations. Standard errors of the averages are given in the parentheses. At the baseline, the labor market transitions are determined by the average of estimated parameters over the sample period, 1979-2008 (except for the years with adverse or positive economic conditions). A worker is said to experience positive economic shocks if his labor market transitions are determined by the set of parameters from the years with positive economic conditions (1997-1999 in this case). Three cases of positive labor market shocks are simulated by imposing a 5-year experience of positive economic conditions at different points of the worker's career: at labor market entry, after 10 years in the labor market, and after 20 years in the labor market. The overall effect of positive economic conditions on earnings is decomposed into two components: employment (δ, λ^0) and earnings($\lambda^+, \lambda^-, F^1$). The estimates are obtained by fixing either the parameters of employment or the parameters of earnings at the average levels during positive economic shocks.

Figure 1: Sample size by education and experience, 1979-2008.



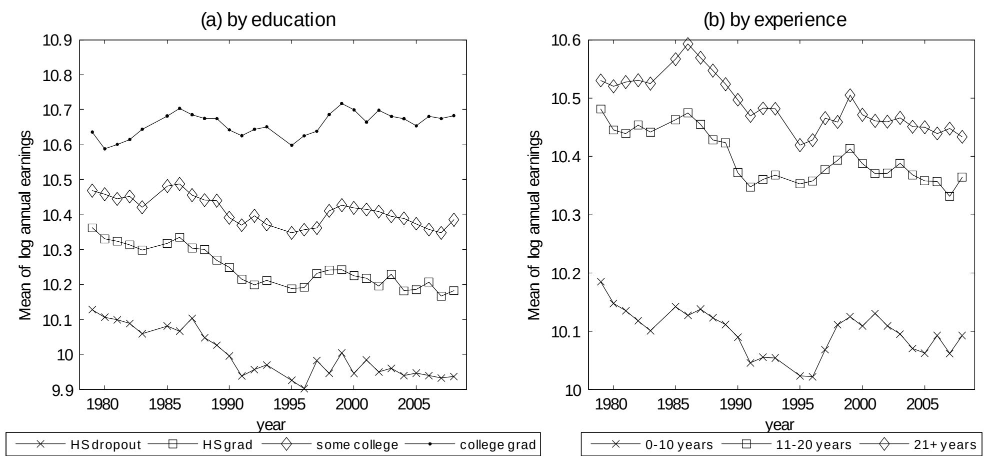
Note: The number of matched observations in the sample are plotted by year and education group (Panel (a)) and by year and experience group (Panel (b)).

Figure 2: Proportion of employed workers in the sample by education and experience, 1979-2008.



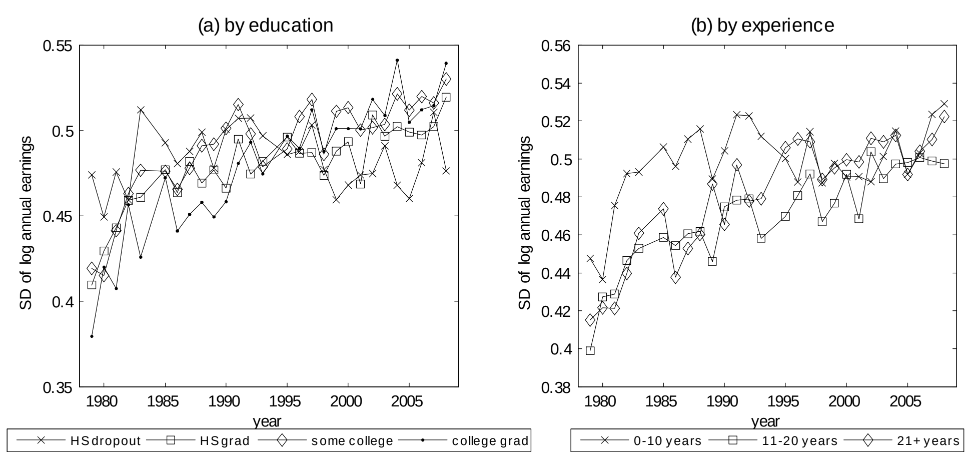
Note: Proportion of the sample who are employed are plotted by year and education group in Panel (a), and by year and experience group in Panel (b).

Figure 3: Average log annual earnings by education and experience,1979-2008.



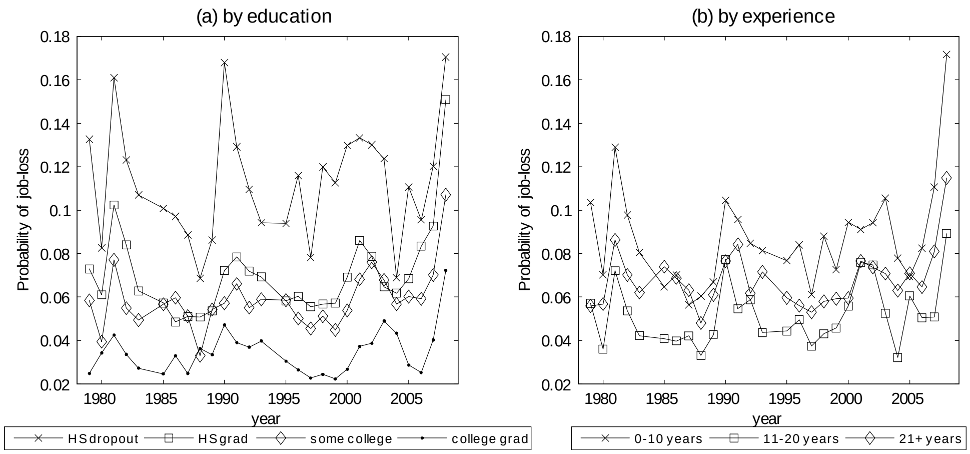
Note: The annual earnings are deflated to 2000 dollars. The averages of log annual earnings by year and education group are given in Panel (a), and by year and experience group in Panel (b).

Figure 4: Standard deviations of log annual earnings by education and experience, 1979-2008.



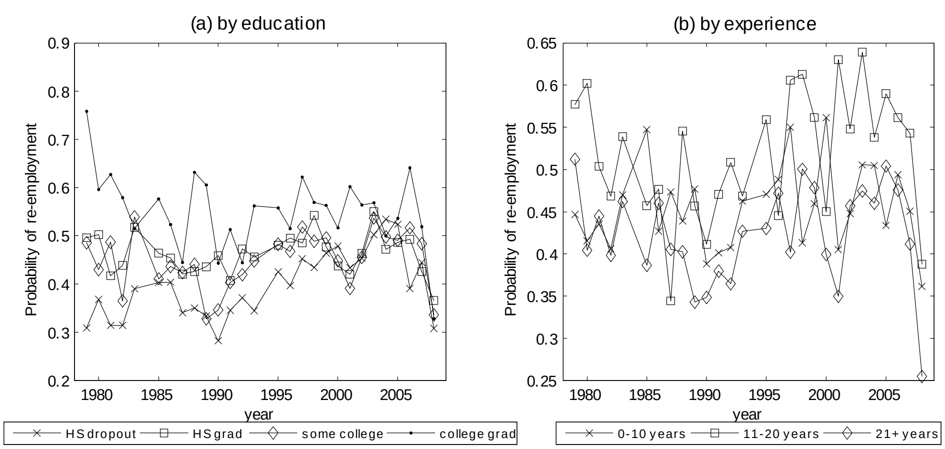
Note: The annual earnings are deflated to 2000 dollars. The standard deviations of log annual earnings by year and education group are given in Panel (a), and by year and experience group in Panel (b).

Figure 5: Probabilities of transition from employment to nonemployment, δ, 1979-2008.



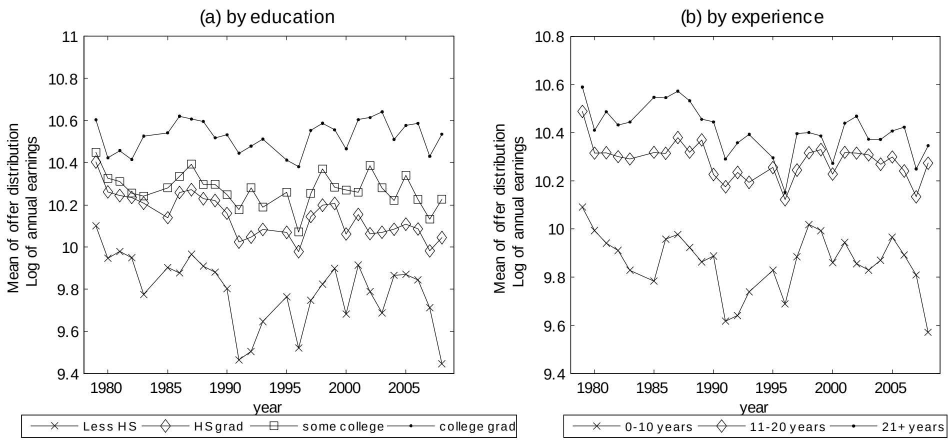
Note: The probabilities of transitioning from employment to nonemployment are estimated by year, education group, and experience group. The estimated parameters are averaged over year and education group (Panel (a)) or year and experience group (Panel (b)).

Figure 6: Probabilities of transition from nonemployment to employment, λ^0, 1979-2008.



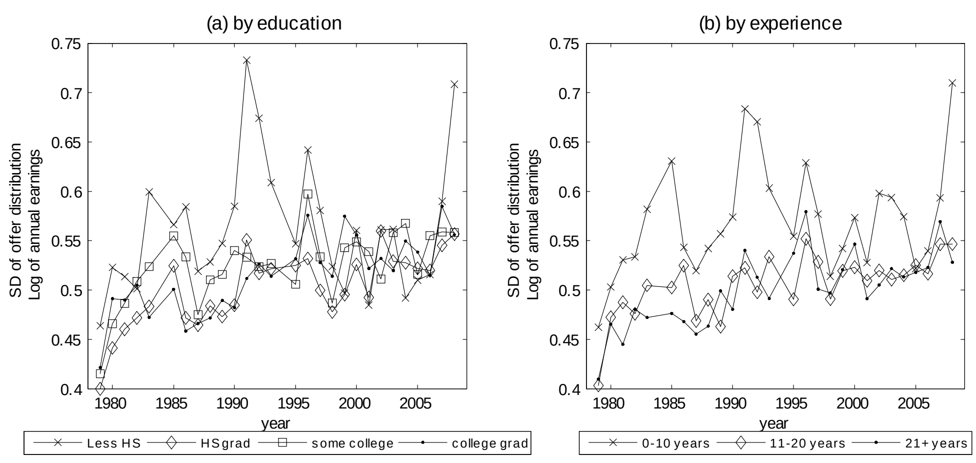
Note: The probabilities of transitioning from employment to nonemployment are estimated by year, education group, and experience group. The estimated parameters are averaged over year and education group (Panel (a)) or over year and experience group (Panel (b)).

Figure 7: Means of the estimated offer distributions of log annual earnings of employed workers, F^1, 1979-2008.



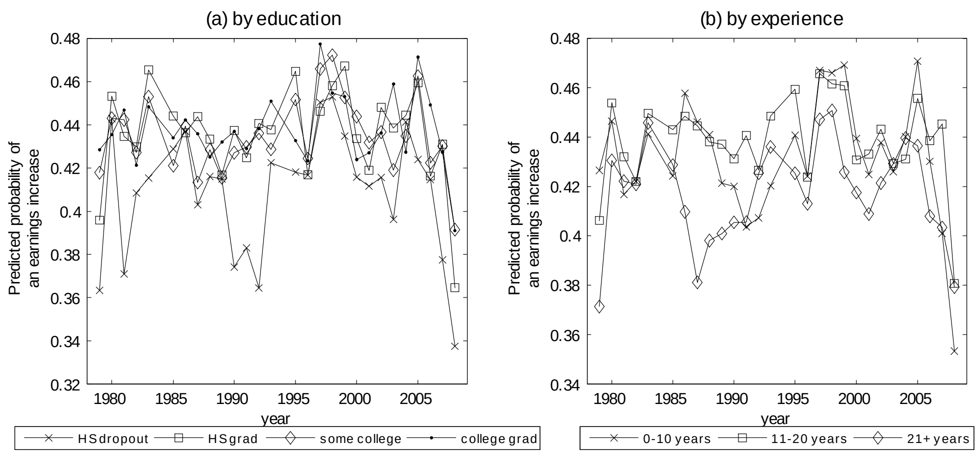
Note: The earnings offer distributions for workers who remain employed for two consecutive periods are estimated by year, eduction group, and experience group. The means of estimated distributions of log annual earnings are averaged over year and education group (Panel (a)) or year and experience group (Panel (b)) .

Figure 8: Standard deviations of the estimated offer distributions of log annual earnings of employed workers, F^1, 1979-2008.



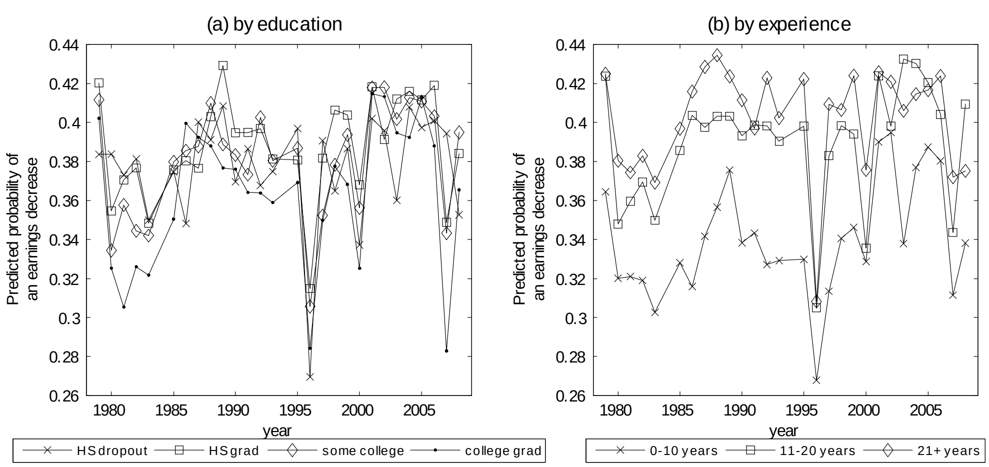
Note: The earnings offer distributions for workers who remain employed for two consecutive periods are estimated by year, eduction group, and experience group. The standard deviations of estimated distributions of log annual earnings are averaged over year and education group (Panel (a)) or over year and experience group (Panel (b)).

Figure 9: The predicted probabilities of earnings increase, 1979-2008.



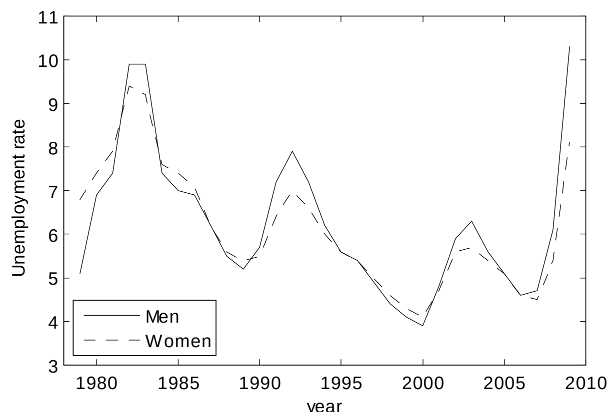
Note: The predicted probabilities of earnings increase are estimated by year, eduction group, and experience group. The probabilities are averaged over year and education group (Panel (a)) or over year and experienc group (Panel (b)).

Figure 10: The predicted probabilities of earnings decrease, 1979-2008.



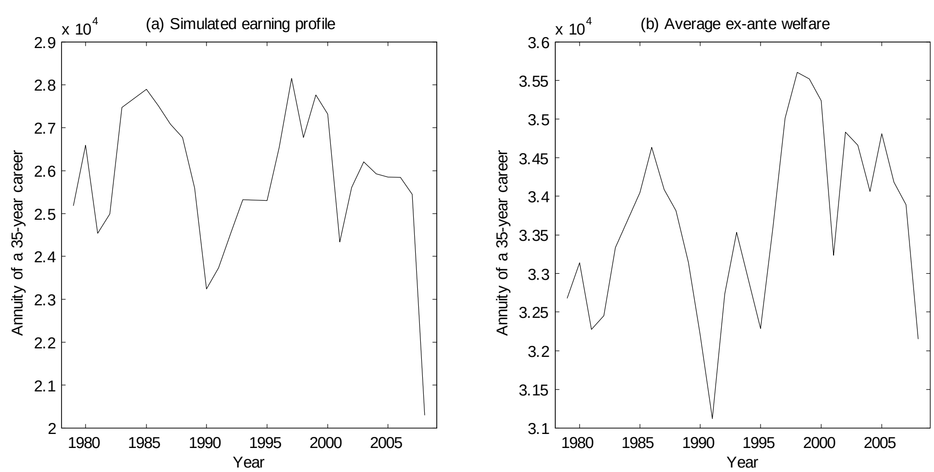
Note: The predicted probabilities of earnings decrease are estimated by year, eduction group, and experience group. The probabilities are averaged over year and education group (Panel (a)) or over year and experienc group (Panel (b)).

Figure 11: Annual unemployment rate for men and women, 1979-2008



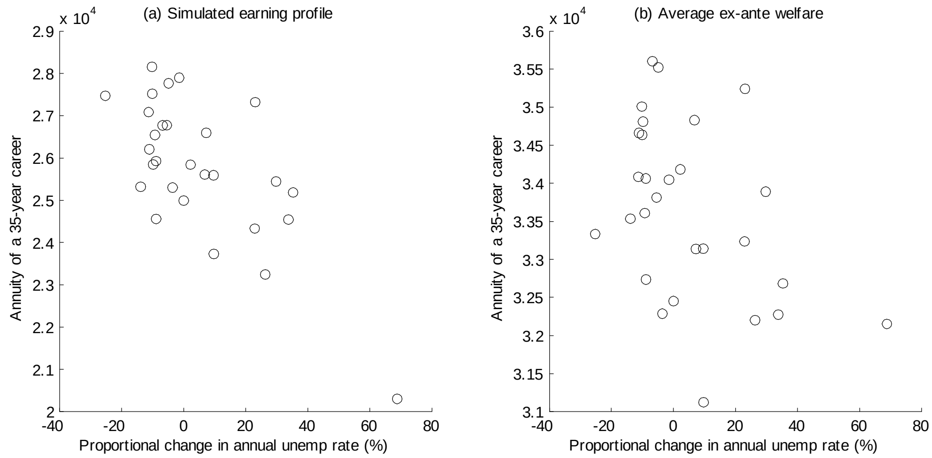
Note: The estimates are from the Bureau of Labor Statistics (BLS).

Figure 12: Measures of economic conditions over time, 1979-2008



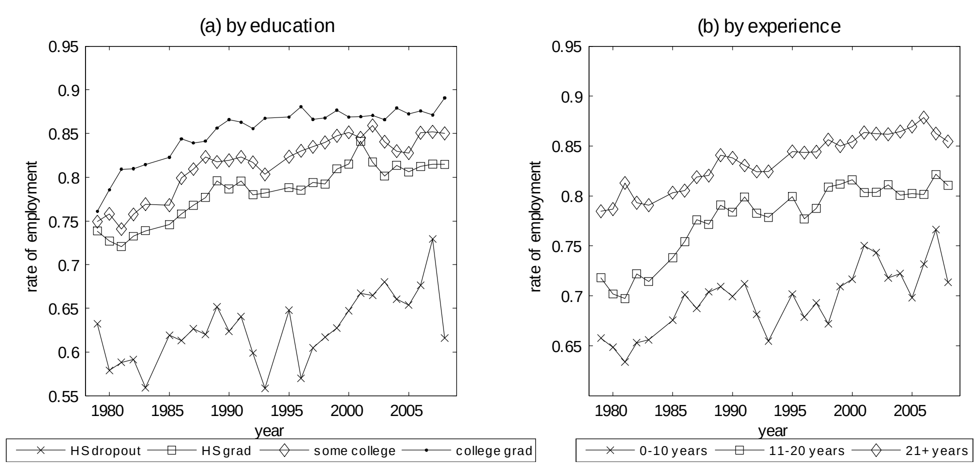
Note: For each year in the sample period, a 35-year earnings profile is simulated for 2,000 times in which labor market transitions are governed by the set model parameters from that year. Annuity of the discounted lifetime earnings (β=0.95) is calculated for each of 2,000 simulated earnings profile, and the average of the 2,000 annuity values is used as a measure of economic conditions. This measure of economic conditions is plotted over time in Panel (a). The second measure of economic conditions is the average ex-ante welfare of individuals in each year of the sample. This measure is plotted over time in Panel (b).

Figure 13: Measures of economic conditions and proportional changes in annual unemployment rates, 1979-2008



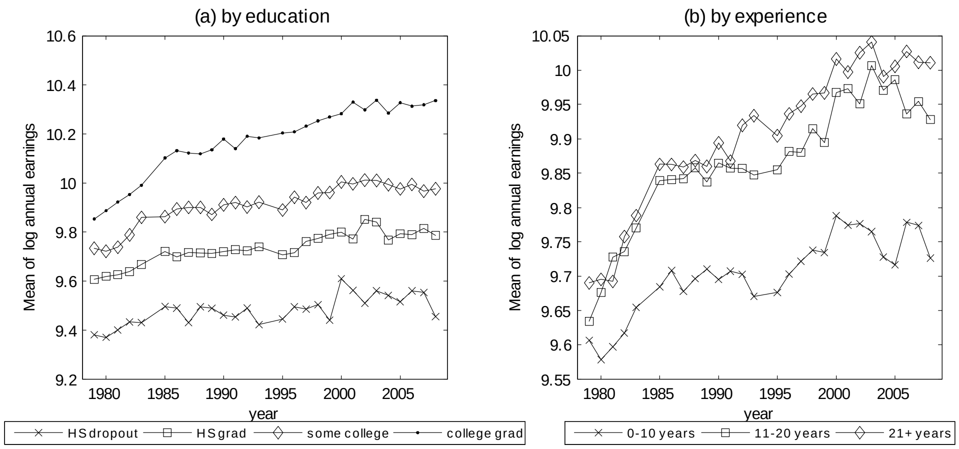
Note: Two measures of economic conditions are plotted against the proportional changes in the BLS estimates of annual unemployment rates for men. For details of the two measures, please refer to the footnote of Figure (12).

Figure 14: Proportion of employed workers in the sample of female workers by education and experience, 1979-2008.



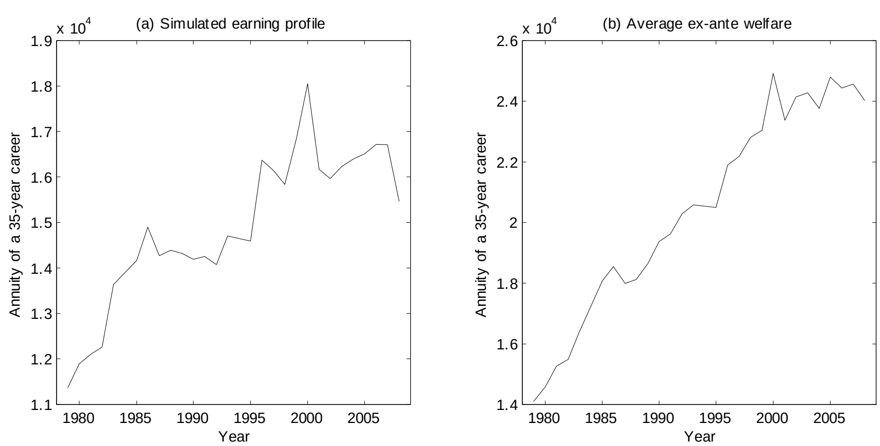
Note: The estimates are based on the matched sample of females in the CPS March Supplements. Proportion of the sample who are employed are plotted by year and education group in Panel (a), and by year and experience group in Panel (b).

Figure 15: Average log annual earnings of female workers,1979-2008.



Note: The estimates are based on the matched sample of females in the CPS March Supplements. The annual earnings are deflated to 2000 dollars. The averages of log annual earnings by year and education group are given in Panel (a), and by year and experience group in Panel (b).

Figure 16: Measures of economic conditions over time for female workers, 1979-2008



Note: The model is estimated using the matched sample of females. Two measures of economic conditions are calculated in the same way as for the sample of males (see the footnote of Figure 12). The two measures are plotted over time.

A Notation Summary

Parameters	Description
δ_t	Probability of transitioning from employment in period t to nonemployment in period $t+1$
λ_t^0	Probability of transitioning from nonemployment in period t to employment in period $t+1$
p_t^+	Fraction of employed workers in period t who receive higher earnings in period $t+1$
p_t^-	Fraction of employed workers in period t who receive lower earnings in period $t+1$
λ_t^+	Arrival rate of a higher earnings offer in period t
λ_t^-	Arrival rate of a higher earnings offer in period t
F_t^1	Offer distribution of period $t+1$ earnings for employed workers in period t
F_t^0	Offer distribution of period $t+1$ earnings for nonemployed workers in period t
b_t	Non-labor income in period t

B Longitudinal Matching of the CPS March Supplements

The rotating panel structure of the CPS allows longitudinal analysis of the sample. In particular, about half of the addresses in the sample (MIS 1-4) will remain in the sample after a year (MIS 5-8). Some individuals of MIS 1-4 in the sample can't be matched forward to the next year because of attrition. In addition, during the sample period of 1980-2010, several changes in the collection of the CPS March supplements affect the matching.

Figure (B.1) plots the number of male civilians 15 years old and over (the solid line). There is a large increase of sample size in 2002. In 2002, the March sample is expanded to obtain more precise estimates of health insurance coverage of low-income children. There are three components to the sample expansion (US Department of Labor (2002)). The first component is the general sample increase in selected states. The increase in sample size affects the basic monthly survey as well as the March Supplements. The second component is called "split-path assignments". Households with children under 18 and non-White members are selected from the February and April sample to receive the March supplemental interview in February or April in place of their regularly scheduled supplements. Only households that would not ordinarily receive the March supplemental interviews are selected for this component of sample expansion, i.e. MIS 4 and 8 of the February sample and MIS 1 and 5 of the April sample. The last component of the sample expansion is called "month-in-sample 9 Assignments". Households with children under 18 and a non-White member in MIS 6, 7, and 8 are selected from sample of the previous November to receive the March supplemental questions. The interviews are conducted in either February or April. The expansion of three components is known as the State Children's Health Insurance Program (SCHIP) sample expansion.

If a household is included in the March file because of the "split-path" or "month-in-sample 9" assignment, it can't be matched forward to next March. To assess the match quality over the sample period, it is desirable to separate non-matches due to attrition and those due to sample expansion. However, those households that are included due to the SCHIP expansion can't be identified directly from the March files. For each March file starting in 2002, only observations in both the March file and the basic monthly file of March of that year are kept for matching (Feng (2008)). Individuals who can't be uniquely identified by household identifiers, household number, and person's line number are also excluded from the sample. Figure (B.1) gives the number of male civilians 15 years old and over who can be uniquely identified in the March file and matched to the basic survey of the same month (dashed line). After excluding observations from the expanded sample, the sample size is consistent over the sample period.

In the first stage of matching, observations of the CPS March supplements from two consecutive years are matched based on household identifiers, household numbers, and personal line numbers (Madrian and Lefgren (1999)). Out of the observations that can be matched to the basic monthly files, those of MIS 1-4 can potentially be matched forward (the solid line in Figure (B.2)). Figure (B.2) plots the number of observations in the matched sample and matching rate by year. The matching rate of a year is the fraction of the MIS 1-4 sample that can be matched forward. The average matching rate is about 72% during the sample period. The matching rates are similar across years except for a dip in 2002.

Because of coding error in the household and individual identifiers, the matches based on those identifiers might not be correct. One way to rule out this type of mismatches is to eliminate matched observations with inconsistency in reported demographic characteristics. But measurement error in the reported demographic characteristics will cause elimination of valid matches. To strike a balance between mismatches due to miscoded identifiers and exclusion of valid matches based on demographic characteristics with reporting errors, Madrian and Lefgren (1999) suggests the use of sex, race, and age to determine the validity of a match. A match is considered valid if the reported gender and race from the two matched periods agree and the difference in reported age between the two periods is less than 3 (inclusive) and greater than -1 (inclusive).

One issue with imposing the consistency criteria is that any change in the reporting of demographic characteristics would lead to violation of the consistency criteria for reasons other than mismatches. Prior to the January 2003 redesign, individuals of mixed race are asked to report a primary race, so the sample can be consistently grouped into three categories based on race: white, black, and other. Since 2003, individuals of mixed race are allowed to report multiple races. To reconcile the difference between these two race variables, the 21-category race variable introduced in 2003 is recoded into three categories to be consistent with the previous years (Table B.1). Even with the recoded race variable, the matched sample of 2002 and 2003 still has a higher rate of inconsistency in race than other years: about 2.7% of the observations in the 2002-2003 matched sample are inconsistent in race, and the average for other years in the sample period is 0.5%[20]. Over the entire sample period, about 4.4% of the observations are dropped from the matched sample due to inconsistency in reported sex, race, and age.

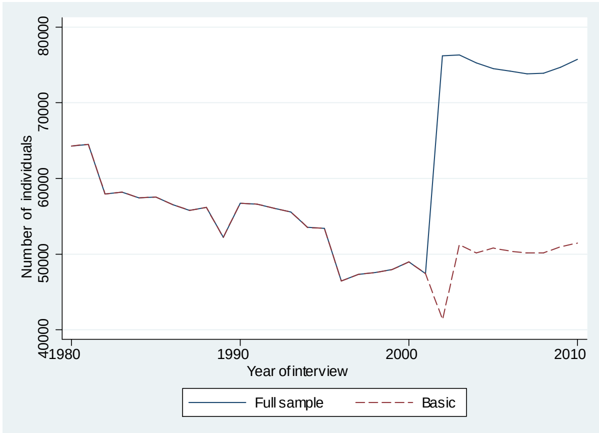
Table B.1: Recode the race variable introduced in the January 2003 CPS redesign.

	Race	Recode
1	White	White
2	Black	Black
3	Amerian Indian (AI)	Other
4	Asian	Other
5	Hawaiian (HP)	Other
6	White-Black	White
7	White-AI	White
8	White-Asian	White
9	White-HP	White
10	Black-AI	Black
11	Black-Asian	Black
12	Black-HP	Black
13	AI-Asian	Other
14	Asian-HP	Other
15	White-Black-AI	White
16	White-Black-Asian	White
17	White-AI-Asian	White
18	White-Asian-HP	White
19	White-Black-AI-Asian	White
20	2 or 3 races	Other
21	4 or 5 races	Other

Note: Recode the 21-category race variable implemented after January 2003 into three categories, White, Black, and Other.

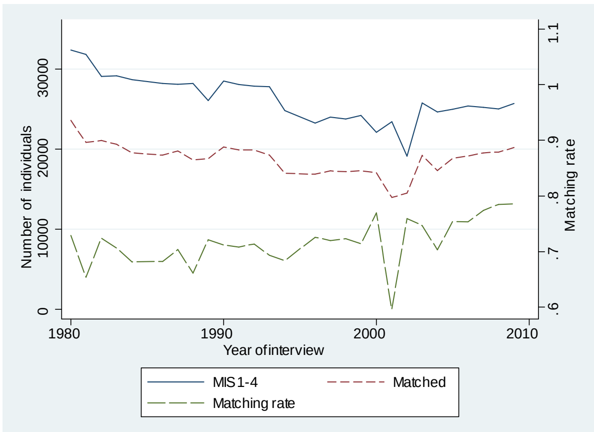
[20] Alternatively, consistency in race can be identified if the reported race in 2002 (White, Black or other) matches at least one of the races reported in 2003. The number of observations in 2002 with inconsistency in race as identified by this method is about 10% less than the recoding method (779 versus 851). The recoding method will be used to identify inconsistency in reported race between 2002 and 2003.

Figure B.1: The number of male civilians 15 years old and over in the March files and the basic monthly files.



Note: The number of male civilians 15 years and older in the March Supplement files and the basic files are reported. The solid line plots the number of male civilians 15 years and older in the March files by year; and the dash line plots the number of male civilians 15 years and older in the March files that can be uniquely identified by the household and individual identifiers and matched to the basic monthly file of March in the same year.

Figure B.2: The matching rate for the sample of civilians 15 years old and over in the March Supplement file.



Note: The solid line gives the number of male civilians 15 years old and over from MIS 1-4 in the March files who can be uniquely identified by the household and individual identifiers and matched to the basic monthly file. These are the individuals who would be eligible for interviews in March of the next year. The series "Matched" plots the number of male civilians 15 years old and over in the matched sample based on the household identifiers, the household number, and the person line number. "Matching rate" is the fraction of male civilians 15 years old and over in the MIS 1-4 sample who could be matched to the sample of the next year based on the household identifiers, the household number, and the person line number.

C Implementing the Estimation Method

The Appendix discusses implementation of the estimation method in details. To simplify computation of the non-stationary model, the model parameters, $\delta_{a,t}$, $F^0_{a,t}$, $\lambda^0_{a,t}$, $\lambda^+_{a,t}(w)$, $\lambda^-_{a,t}(w)$, and $F^1_{a,t}$, are constrained to be constant within each education and experience group. The experience level is denote by $a \in [a_i, a_{i+1})$, where i indicates the experience groups. In the matched CPS sample, four education categories (less than high school, high school graduates, some college, and college graduates) and three experience categories (0-10 years, 11-20 years, and 21 and more years) are defined.

Under the simplifying assumptions, the rate of job loss for workers of experience group i and education group j, $\delta_{i,j,t}$, is estimated from the fraction of employed workers of experience group i and education group j in period t who become nonemployed in period $t+1$; and the rate of re-employment for workers of experience group i and education group j in period t, $\lambda^0_{i,j,t}$, is the fraction of nonemployed workers of experience group i and education group j who becomes employed in period $t+1$. Let $E_{i,j,t}$ and $N_{i,j,t}$ be the number of employed and nonemployed workers of education group j in period t with experience level within the i-th experience group, respectively. For workers in experience group i and education group j, define $EN_{i,j,t}$ as the number of employed workers in period t who become nonemployed in period $t+1$, and define $NE_{i,j,t}$ as the number of nonemployed workers in period t who become employed in period $t+1$. Under the simplifying assumption, the moment conditions for the rates of job loss and re-employment become:

$$\delta_{i,j,t} = \frac{EN_{i,j,t}}{E_{i,j,t}}, \tag{C.1}$$

$$\lambda^0_{i,j,t} = \frac{NE_{i,j,t}}{N_{i,j,t}}. \tag{C.2}$$

The earnings offer distribution of newly employed workers of education group j and experience group i in period t, $F^0_{i,j,t}(w)$, is estimated by the non-parametric kernel density method. The estimation uses the period $t+1$ earnings of workers in education group j and experience group j who transition from nonemployment to employment between periods t and $t+1$.

To estimate the offer distributions and the arrival rates of offers, the flow balance equation of employment is first stated under the simplifying assumptions. Let $G_{i,j,t}(w)$ denote the cumulative density function of cross-sectional earnings distribution in the sample of workers with experience i and education j in period t. The stock of employed workers of experience group i and education group j in period t is defined as $G_{i,j,t}(w)E_{i,j,t} \equiv \sum_{a=a_i}^{a_{i+1}-1} G_{a,j,t}(w)E_{a,j,t}$. The difference between the stock of employed workers with experience level $a \in [a_i+1, a_{i+1}+1)$ and education j earning less than w in period $t+1$ and the stock of employed workers in experience group i and education group j earning less than w in period t is given by

$$\begin{aligned}
\Delta G_{i,j,t}(w)E_{i,j,t} &= \sum_{a=a_i}^{a_{i+1}-1} G_{a+1,j,t+1}(w)E_{a+1,j,t+1} - \sum_{a=a_i}^{a_{i+1}-1} G_{a,j,t}(w)E_{a,j,t} \\
&= \left\{G_{i,j,t+1}(w)E_{i,j,t+1} + G_{a_{i+1},j,t+1}(w)E_{a_{i+1},j,t+1} - G_{a_i,j,t+1}(w)E_{a_i,j,t+1}\right\} \\
&\quad - G_{i,j,t}(w)E_{i,j,t}. \qquad \text{(C.3)}
\end{aligned}$$

The equality follows because $\sum_{a=a_i}^{a_{i+1}-1} G_{a,j,t}(w)E_{a,j,t}(w)$ can be written as $G_{i,j,t}(w)E_{i,j,t}$. An alternative expression of the change in the stock of employed workers follows from Equation (10) under the simplifying assumption

$$\begin{aligned}
\Delta G_{i,j,t}(w)E_{i,j,t} &= N_{i,j,t}\lambda^0_{i,j,t}F^0_{i,j,t}(w) \\
&\quad + E_{i,j,t}\lambda^-_{i,j,t}\left[1 - G_{i,j,t}(w)\right]F^1_{i,j,t}(w) \\
&\quad - E_{i,j,t}\delta_{i,j,t}G_{i,j,t}(w) \\
&\quad - E_{i,j,t}G_{i,j,t}(w)\lambda^+_{i,j,t}\left(1 - F^1_{i,j,t}(w)\right).
\end{aligned}$$

Rewriting the equation gives an expression for the earnings offer distribution of workers who remain employed in two consecutive years, $F^1_{i,j,t}(w)$, under the simplifying assumptions

$$\begin{aligned}
F^1_{i,j,t}(w) &= \frac{\Delta G_{i,j,t}(w)E_{i,j,t} + E_{i,j,t}\delta_{i,j,t}G_{i,j,t}(w) + E_{i,j,t}\lambda^+_{i,j,t}G_{i,j,t}(w) - N_{i,j,t}\lambda^0_{i,j,t}F^0_{i,j,t}(w)}{E_{i,j,t}\lambda^-_{i,j,t}\left[1 - G_{i,j,t}(w)\right] + E_{i,j,t}\lambda^+_{i,j,t}G_{i,j,t}(w)} \\
&= \frac{\frac{\Delta G_{i,j,t}(w)E_{i,j,t}}{E_{i,j,t}} + \delta_{i,j,t}G_{i,j,t}(w) + \lambda^+_{i,j,t}G_{i,j,t}(w) - \frac{N_{i,j,t}}{E_{i,j,t}}\lambda^0_{i,j,t}F^0_{i,j,t}(w)}{\lambda^-_{i,j,t}\left[1 - G_{i,j,t}(w)\right] + \lambda^+_{i,j,t}G_{i,j,t}(w)}. \qquad \text{(C.4)}
\end{aligned}$$

The term $\frac{\Delta G_{i,j,t}(w)E_{i,j,t}}{E_{i,t}}$ can estimated from the earnings data. Let $G^{+1}_{i,j,t}(w)$ denote the earnings distribution of workers with experience level $a \in [a_i+1, a_{i+1}+1)$ and education j in year $t+1$. Let $E^{+1}_{i,j,t}$ denote the number of employed workers with experience level $a \in [a_i+1, a_{i+1}+1)$ and education j in year $t+1$. Therefore, the change in earnings distribution can be expressed as

$$\Delta G_{i,j,t}(w)E_{i,j,t} = G^{+1}_{i,j,t}(w)E^{+1}_{i,j,t} - G_{i,j,t}(w)E_{i,j,t}.$$

Divide both side by $E_{i,j,t}$, the equation becomes

$$\frac{\Delta G_{i,j,t}(w)E_{i,j,t}}{E_{i,j,t}} = G^{+1}_{i,j,t}(w)\frac{E^{+1}_{i,j,t}}{E_{i,j,t}} - G_{i,j,t}(w). \tag{C.5}$$

The earnings offer distribution can be estimated from Equation (C.4) given the arrival rates of offers, $\lambda^{+}_{i,j,t}$ and $\lambda^{-}_{i,j,t}$. The arrival rates can be estimated given the earnings offer distribution of workers who remain employed for two consecutive periods and the rates of earnings increase and decrease. For employed workers with experience level i and education j in period t, the probability of receiving higher earnings in period $t+1$ is

$$p^{+}_{i,j,t} = \lambda^{+}_{i,j,t} \cdot \int_{\underline{w}^{1}_{j,t}}^{\overline{w}^{1}_{i,j,t}} \left[1 - F^{1}_{i,j,t}(w)\right] dG_{i,j,t}(w);$$

and the probability of receiving lower earnings in period $t+1$ is

$$p^{-}_{i,j,t} = \lambda^{-}_{i,j,t} \cdot \int_{\underline{w}^{1}_{j,t}}^{\overline{w}^{1}_{i,j,t}} F^{1}_{i,j,t}(w) dG_{i,j,t}(w).$$

In the model, employed workers in period t can transition into four possible states in period $t+1$: nonemployment, employment with higher earnings, employment with lower earnings, and employment without change in earnings. The probability of transitioning into either one of these four states should be one. Alternatively, the probability of transitioning into nonemployment or employment with different earnings should be less than one (inclusive), or

$$0 \le \lambda^{+}_{i,j,t}\left[1 - F^{1}_{i,j,t}(w)\right] + \lambda^{-}_{i,j,t}F^{1}_{i,j,t}(w) \le 1 - \delta_{i,j,t}$$

Since $\lambda^{+}_{i,j,t}\left[1 - F^{1}_{i,j,t}(w)\right] + \lambda^{-}_{i,j,t}F^{1}_{i,j,t}(w) \le \max\{\lambda^{+}_{i,j,t}, \lambda^{-}_{i,j,t}\}$, a sufficient condition would be that both $\lambda^{+}_{i,j,t}$ and $\lambda^{-}_{i,j,t}$ must be less than $1-\delta_{i,j,t}$ (inclusive) and greater than zero (inclusive). Under this restriction, the moment conditions for the arrival rates of offers are

$$\left\{\begin{array}{c} \lambda^{+}_{i,j,t} = \max\left\{0, \min\left\{1-\delta_{i,j,t}, \frac{p^{+}_{i,j,t}}{\int_{\underline{w}^{1}_{j,t}}^{\overline{w}^{1}_{i,j,t}}\left[1-F^{1}_{i,j,t}(w)\right]dG_{i,j,t}(w)}\right\}\right\} \\ \lambda^{-}_{i,j,t} = \max\left\{0, \min\left\{1-\delta_{i,j,t}, \frac{p^{-}_{i,j,t}}{\int_{\underline{w}^{1}_{j,t}}^{\overline{w}^{1}_{i,j,t}} F^{1}_{i,j,t}(w)dG_{i,j,t}(w)}\right\}\right\} \end{array}\right. . \tag{C.6}$$

It is very likely that a small change in earnings over two period is due to measurement error of earnings data. To limit misclassification of earnings changes due to measurement errors, $p^{+}_{i,j,t}$ ($p^{-}_{i,j,t}$) is the fraction of employed workers with experience i and education j in period t whose earnings in period $t+1$ are at least 2% higher (lower) than his earnings in period t.

To summarize, the estimation proceeds as the follows:

1. $G_{i,j,t}$ is estimated by the non-parametric kernel density method for each year in the sample period and each experience and education group, or $\widehat{G}_{i,j,t}$.

2. $F^{0}_{i,j,t}$ is estimated from the full sample using kernel density function for each experience and education group, or $\widehat{F^{1}}_{i,j,t} = \widehat{F^{0}}_{i,j}$ for all t.

3. Estimate $\frac{\Delta G_{i,j,t}(w)E_{i,j,t}}{E_{i,j,t}}$ using equation (C.5). $G_{i,j,t}(w)$ is estimated non-parametrically from step (1). Estimate $G^{+1}_{i,j,t}(w)$ using earnings of workers with experience level $a \in [a_i+1, a_{i+1}+1)$ and education j in period $t+1$. $E_{i,j,t}$ is the number of employed workers of education group j and experience group i in period t; and $E^{+1}_{i,j,,t}$ is the number of employed workers of experience level $a \in [a_i+1, a_{i+1}+1)$ and education j in period $t+1$.

4. Estimate the rates of job loss and re-employment, $\delta_{i,j,t}$ and $\lambda^{0}_{i,j,t}$, using the moment conditions in equations (C.1) and (C.2). They are estimated for each year in the sample period and each education and experience group.

5. $\underline{w}^{1}_{j,t}$ is the minimal annual earnings among employed workers within each education group in each year of the sample period.

6. Solve the fixed-point equations system (Equations C.4 and C.6) by iterations to obtain estimates for $F^{1}_{i,j,t}$, $\lambda^{+}_{i,j,t}$, and $\lambda^{-}_{i,j,t}$.

D Tables and Figures

Table D.1: Simulated lifecycle effect of negative economic shocks by education using alternative definitions of employment.

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed if >39 wks			Employed if >13 wks		
	Years 1-5	Years 11-15	Years 21-25	Years 1-5	Years 11-15	Years 21-25
A. Less than HS						
All	-4.84	-0.99	-4.14	-7.28	-1.41	-3.64
δ, λ^0	-3.67	0.49	-2.86	-6.49	0.30	-2.25
$\lambda^+, \lambda^-, F^1$	-1.10	-0.23	-0.97	-1.13	-1.34	-1.46
B. HS grads						
All	-5.76	-4.98	-2.58	-4.47	-4.88	-2.28
δ, λ^0	-5.66	-3.23	-1.82	-4.06	-2.73	-1.35
$\lambda^+, \lambda^-, F^1$	-0.39	-1.95	-0.66	-1.09	-2.49	-0.89
C. Some college						
All	-2.46	-2.75	-1.31	-2.13	-2.17	-1.46
δ, λ^0	-1.95	-2.56	-0.83	-1.48	-1.98	-0.80
$\lambda^+, \lambda^-, F^1$	-0.73	0.06	-0.40	-0.92	-0.09	-0.73
D. College grads						
All	-2.45	-2.69	-0.50	-4.20	-1.12	-0.37
δ, λ^0	-3.04	-2.81	-0.76	-4.54	-1.09	-0.81
$\lambda^+, \lambda^-, F^1$	0.48	0.04	0.30	0.23	-0.18	0.40

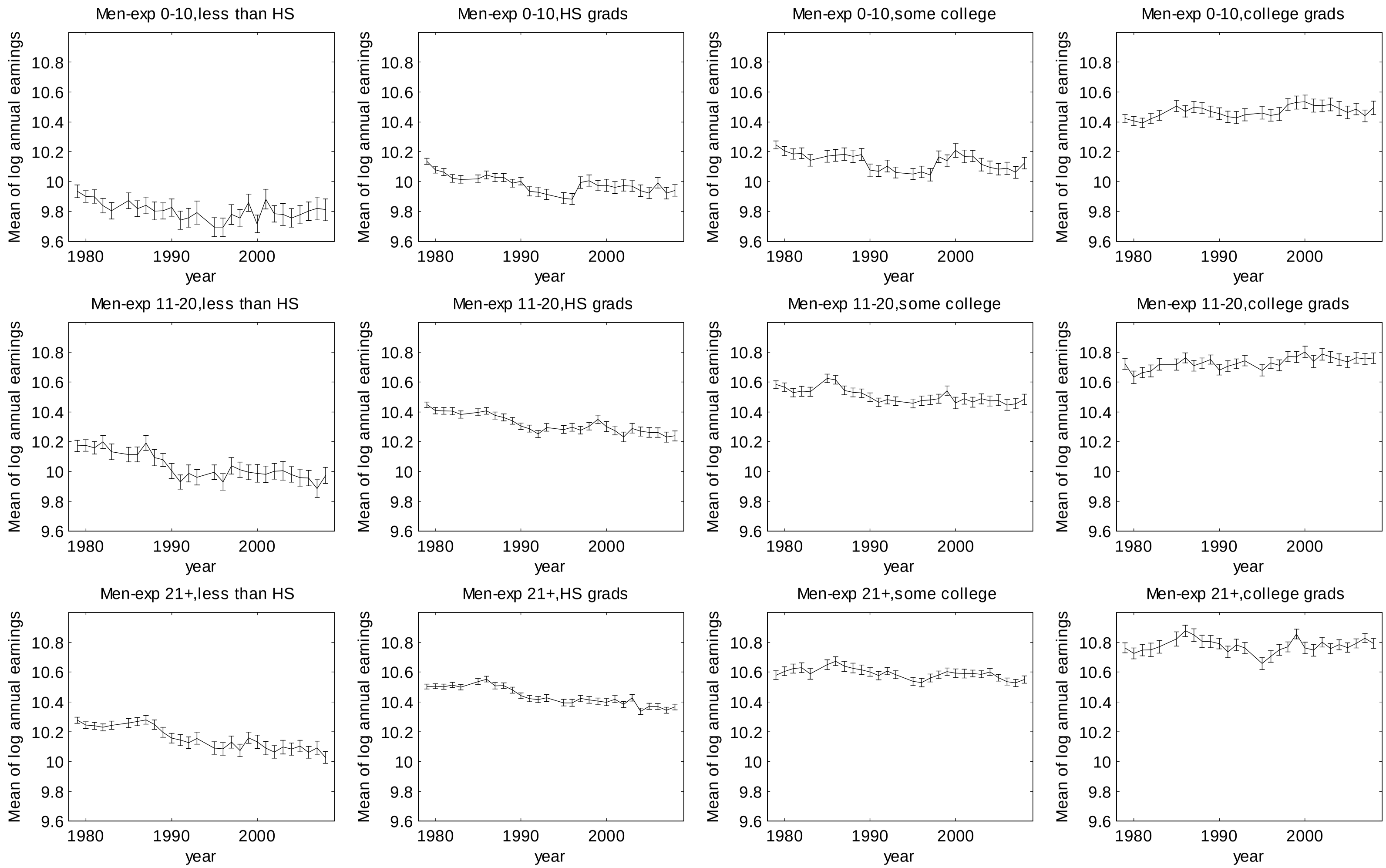
Note: The estimates in columns (1)-(3) are based on the sample that defines a worker as employed for a year if he has worked for more than 39 weeks of the year. The estimates in columns (4)-(6) are based on the sample that defines a worker as employed for a year if he has worked for more than 13 weeks of the year. Please refer to the footnote of Figure (3) for details of the simulation.

Table D.2: Simulated lifecycle effect of positive economic shocks by education using alternative definitions of employment.

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed if >39 wks			Employed if >13 wks		
	Years 1-5	Years 11-15	Years 21-25	Years 1-5	Years 11-15	Years 21-25
A. Less than HS						
All	6.19	3.35	0.86	2.92	1.93	-0.11
δ, λ^0	6.05	3.21	1.19	2.58	1.41	0.14
$\lambda^+, \lambda^-, F^1$	0.73	1.33	0.01	0.72	0.79	-0.14
B. HS grads						
All	1.24	1.04	0.71	1.19	0.70	0.21
δ, λ^0	0.93	1.14	0.87	0.76	0.34	0.29
$\lambda^+, \lambda^-, F^1$	0.46	0.16	0.08	0.40	0.35	-0.06
C. Some college						
All	4.22	1.36	0.47	2.25	0.91	0.29
δ, λ^0	3.54	1.09	0.47	1.45	0.43	0.19
$\lambda^+, \lambda^-, F^1$	0.65	0.56	0.15	0.68	0.72	0.11
D. College grads						
All	1.79	1.59	0.51	-0.27	1.48	0.53
δ, λ^0	0.27	0.47	0.24	-1.72	0.17	0.14
$\lambda^+, \lambda^-, F^1$	1.42	1.11	0.29	1.59	1.27	0.36

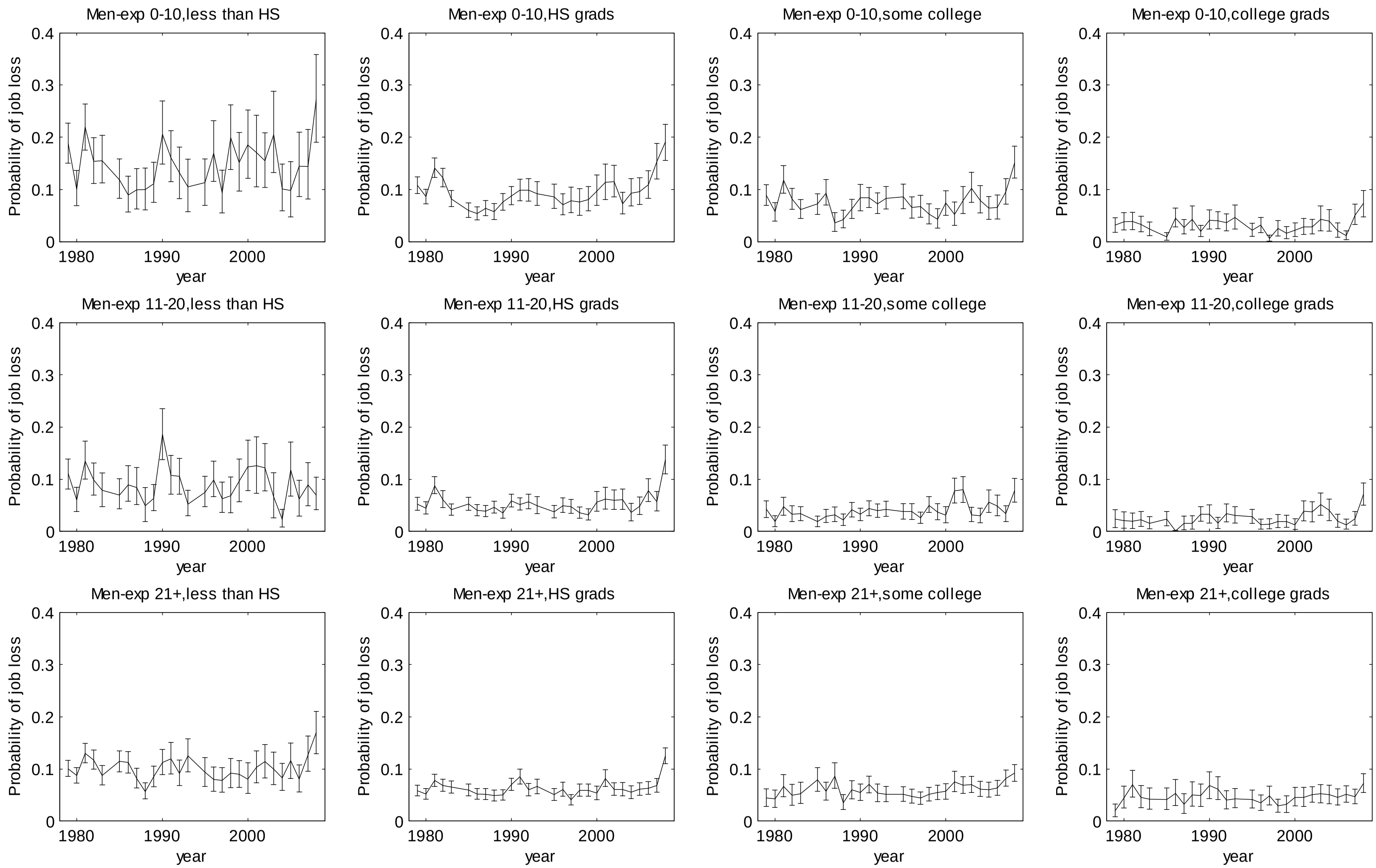
Note: The estimates in columns (1)-(3) are based on the sample that defines a worker as employed for a year if he has worked for more than 39 weeks of the year. The estimates in columns (4)-(6) are based on the sample that defines a worker as employed for a year if he has worked for more than 13 weeks of the year. Please refer to the footnote of Figure (4) for details of the simulation.

Figure D.1: Average annualized earnings by year, 1979-2008



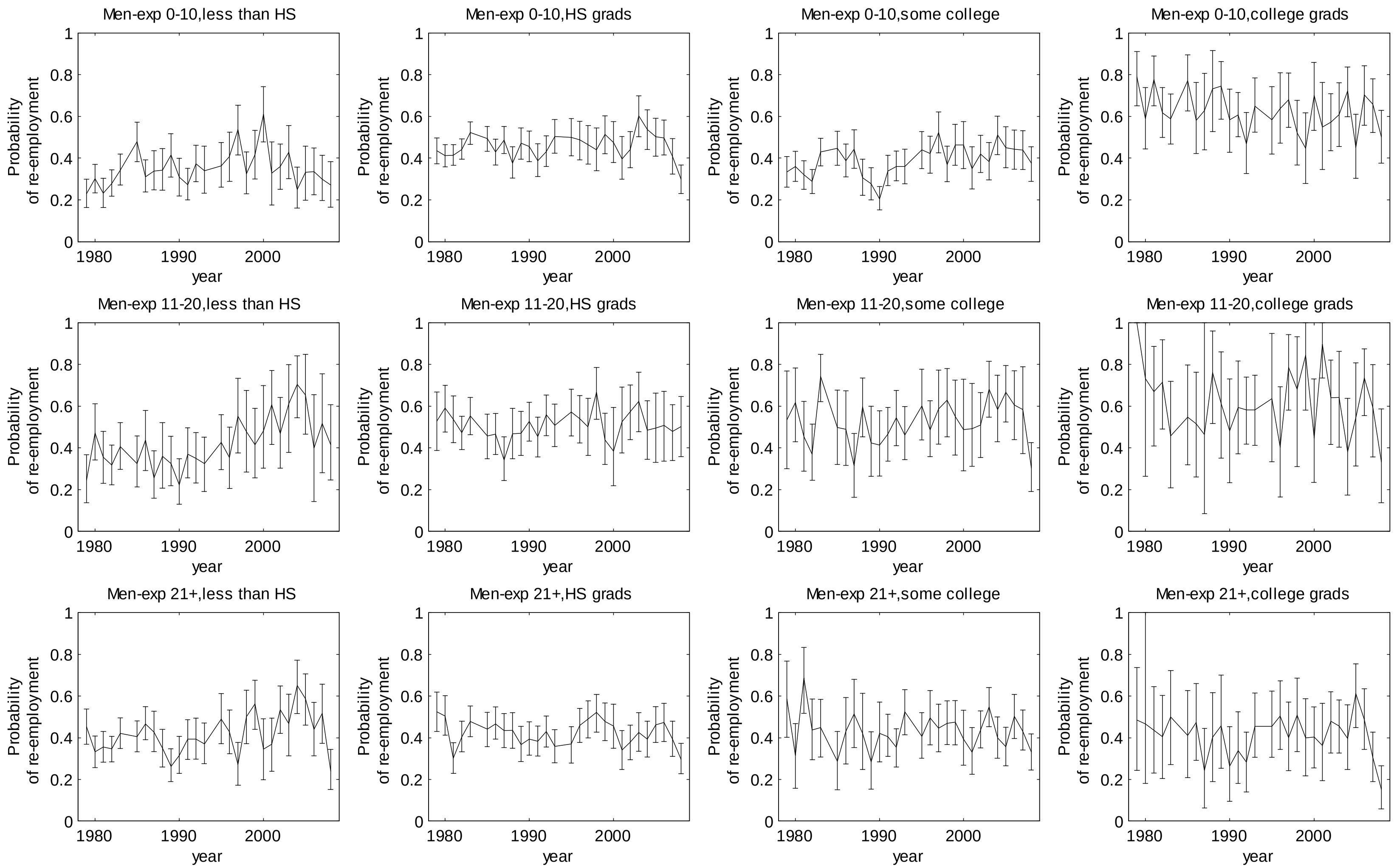
Note: Sample means of log annual earnings deflated to 2000 dollar are given by year, education and experience. The two-standard-deviation bands are plotted for each estimate.

Figure D.2: Probabability of transitioning from employment to nonemployment with bootstrapped 90 confidence interval, 1979-2008



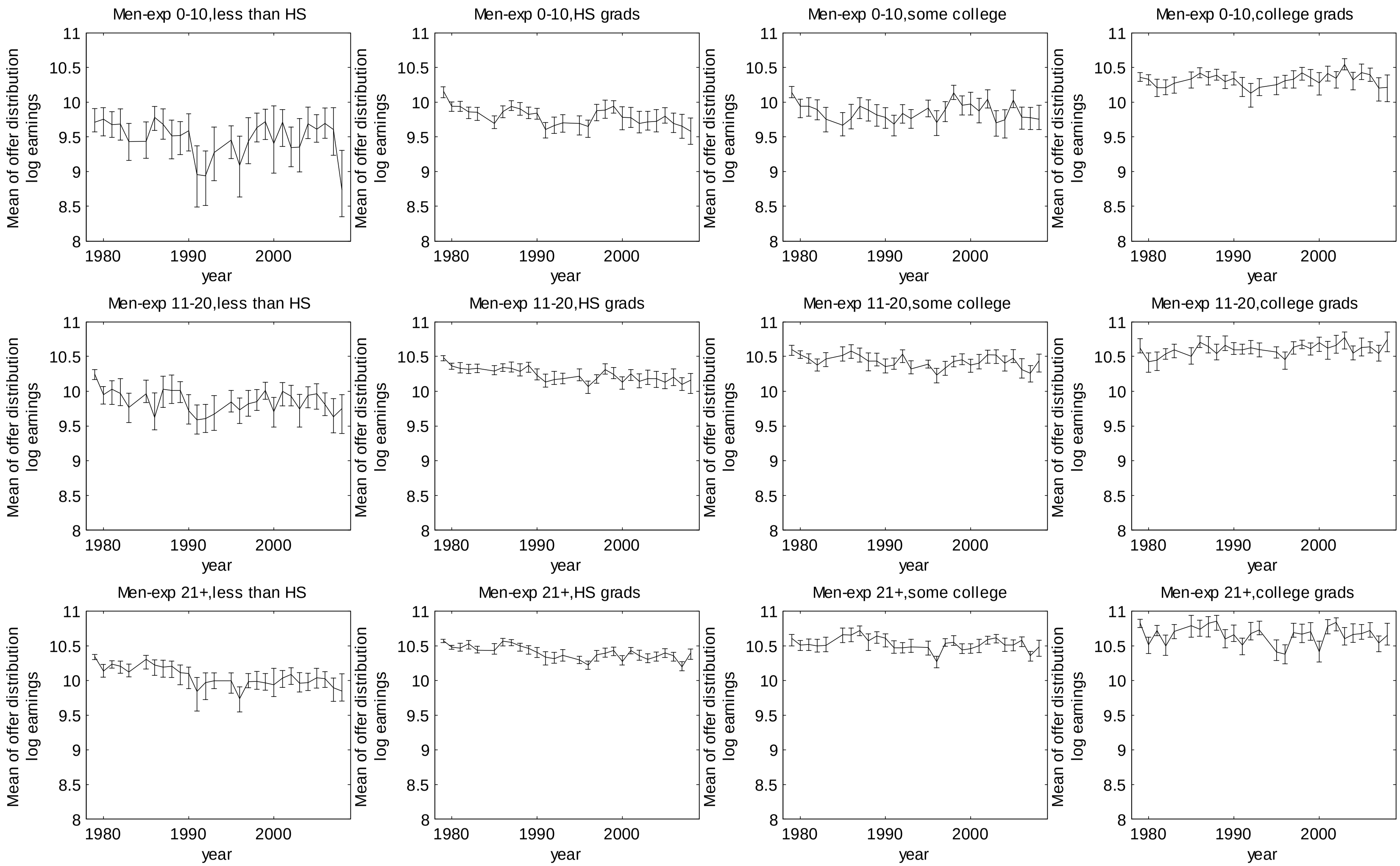
Note: Probabilities of transitioning from employment to nonemployment are plotted by year, education, and experience. Bootstrapped 90 percent confidence intervals based on 2,000 draws are also included.

Figure D.3: Probability of transitioning from nonemployment to employment, 1979-2008



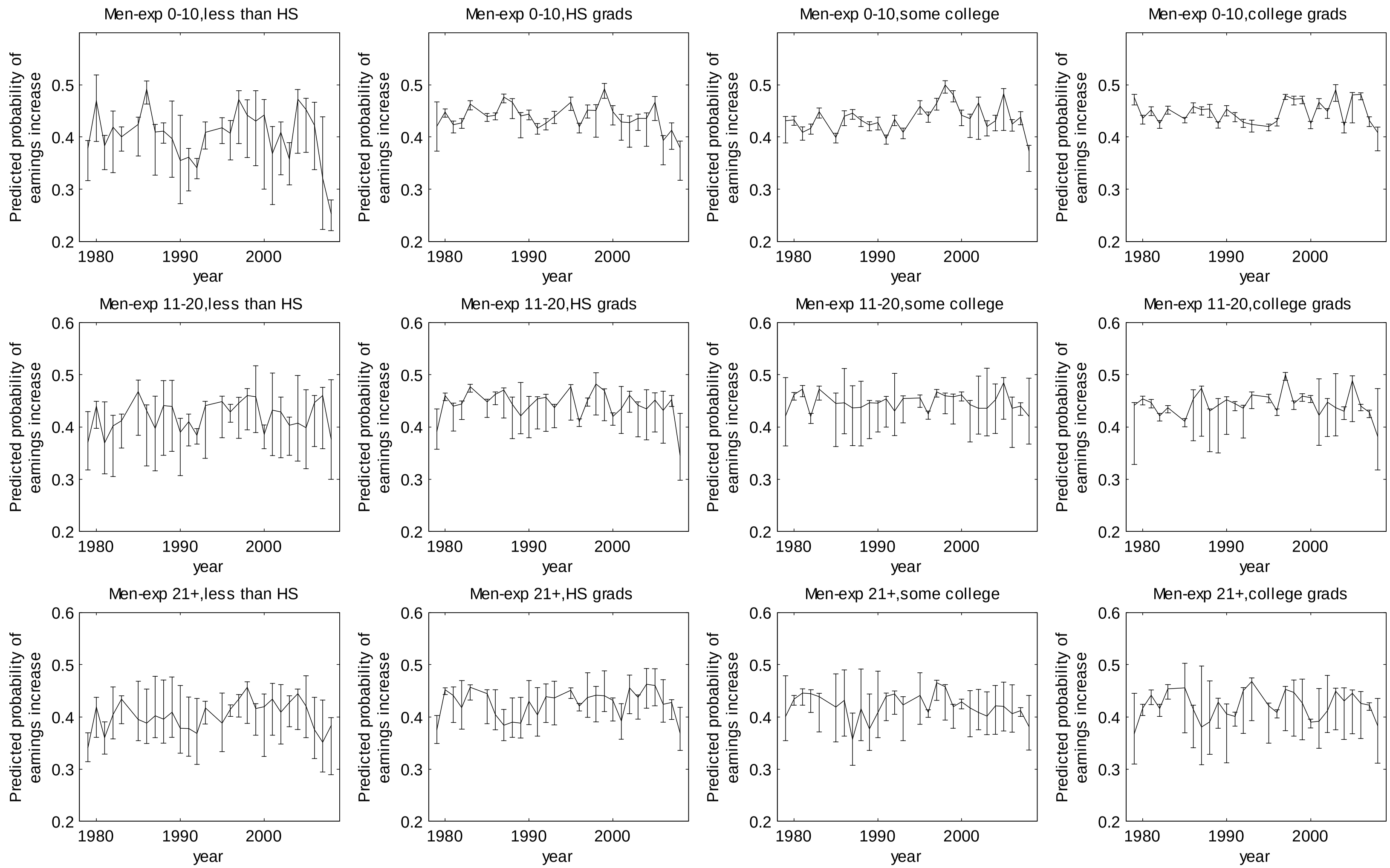
Note: Probabilities of transitioning from nonemployment to employment are plotted by year, education, and experience. Bootstrapped 90 percent confidence intervals based on 2,000 draws are also included.

Figure D.4: Mean of the earning offer distribution with bootstrapped 90 confidence interval, F, 1979-2008



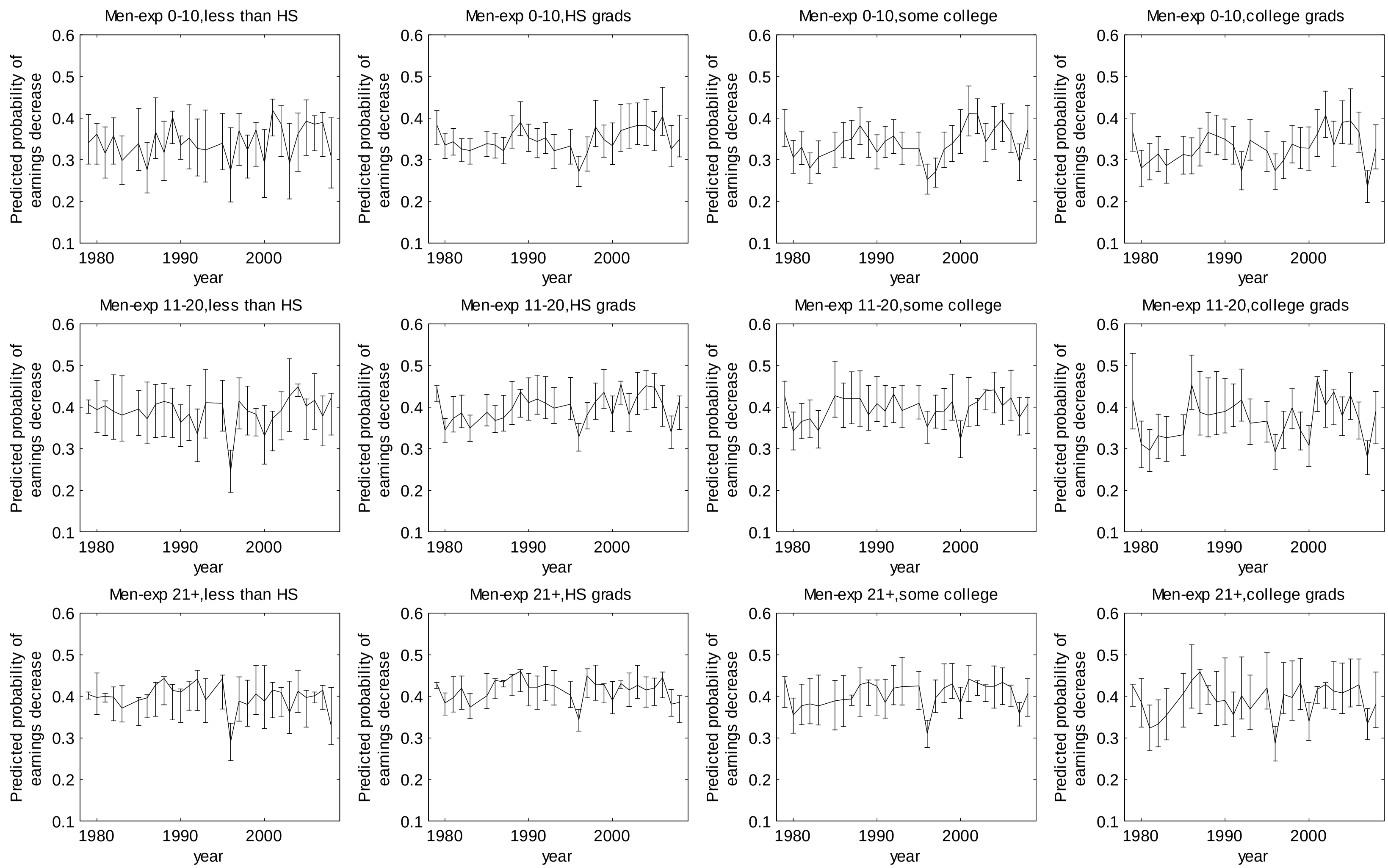
Note: Means of earnings offer distributions of employed workers are plotted by year, education, and experience. Bootstrapped 90 percent confidence intervals based on 2,000 draws are also included.

Figure D.5: Predicted probabilities of earnings increase with 90 percent confidence interval, 1979-2008



Note: Predicted probabilities of earnings increase are plotted by year, education, and experience. Bootstrapped 90 percent confidence intervals based on 2,000 draws are also included.

Figure D.6: Predicted probabilities of earnings decrease with 90 percent confidence interval, 1979-2008



Note: Predicted probabilities of earnings decrease are plotted by year, education, and experience. Bootstrapped 90 percent confidence intervals based on 2,000 draws are also included.