The Changing Pattern of Wage Growth for Low Skilled Workers

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1. Introduction

One of the fundamental facts in labor economics is that, on average, wages tend to rise rapidly early in a worker's career. Since wage growth during the early stages of the one's career provides a potential pathway out of poverty, it is important to understand what causes this wage progression and how it is affected by changes in the overall economy. In this chapter, we focus on the key components that determine an individual's early career wage growth and how these factors have changed for less skilled workers over the last twenty years. In particular, we examine the relative importance of accumulating work experience as compared to the quality of job matches in influencing wage growth over this time period.

The importance of experience accumulation on wage growth is a particularly relevant concern for policy makers in light of the reforms to the tax and welfare system that have taken place since the early 1990s. The expansion of the Earned Income Tax Credit (EITC) and the Personal Responsibility and Work Opportunity Act (PROWORA), were specifically designed to encourage low skilled individuals to enter the workforce. Perhaps as a result of these policies, the labor force participation rates of men and women with low levels of schooling did in fact increase during the 1990s. However, entry-level wages for low-skilled workers are low and have been stagnant over the last twenty five years.[2] This calls into question whether these programs can really do much to alleviate poverty.

Although starting wages of low skill workers are low, they potentially increase with experience. Therefore, the success of tax and welfare reforms in reducing poverty rests critically upon the extent to which experience accumulation increases the wages of low skilled individuals. To highlight the importance of experience accumulation, consider Figure 1, which shows the extent to which wages increase with age.[3] Between ages 18 and 28 wages grow by about 45 percent, from $6.90 to $10 per hour, for men with no college. For a single earner in a 4 person household working 40 hours per week, 50 weeks per year, such a wage gain would actually move the family out of poverty. Clearly, labor force experience has the potential to substantially raise wages.

However, labor market experience is not the only potentially important source of wage growth for younger workers. Robert Topel and Michael Ward (1992) show that for workers who entered the labor market in the late 1950s, earnings gains at job switches accounted for about a third of early career earnings growth. Arguably, the earnings increases associated with job switches reflect improvements in the quality of job matches over an individual's career. Concerns about job match quality might be especially important for low skill workers, because they have less stable employment patterns. As a result, some observers have expressed concern that difficulties in holding jobs, and in moving to better ones (Harry Holzer and Robert LaLonde, 1999), retards wage growth for low skill workers.

One would expect the job match process to change over the business cycle in ways that would lead this component of wage growth to be highly cyclical. First, it is likely to be much easier to find a good job during a boom than during a recession. Second, since layoffs are typically associated with wage declines one would expect the higher rate of layoffs during recessions to depress wage growth. This suggests that an analysis of the changing pattern of wage growth should disentangle the importance of finding a good job, or *matching*, from the importance of work experience in determining wage growth.

Despite the centrality of early career wage *growth* to labor economics, it is surprising how little we actually know about the factors that determine wage growth, their cyclical properties, and how they have changed over time.[4] The primary purpose of this chapter is to document how wage growth has changed over the last twenty years for low skilled workers and to understand which components have driven these changes. To motivate our analysis we present some basic facts concerning early career wage aged growth for low skilled workers. Figure 2 plots hourly wage growth for workers aged 18-28 who did not attend college using the matched Current Population Survey (CPS) Outgoing Rotation Group data.[5] This group, which contains both men and women, acts as our primary reference group throughout our analysis. The data shows that young workers' wages increase about 4.5 percent per year, on average. Figure 2 also makes clear that wage growth varies considerably over time and may be related to the business cycle. Wage growth was about 3 percent per year during 1980-1983, 1990-1994, and 2002-2004, the years that unemployment rates were high and rising. In contrast, wage growth averaged 6 percent during 1984-1987 and 1995-2001, the years that unemployment was low and falling.[6]

For our main analysis we use data from the Survey of Income and Program Participation (SIPP) covering the years 1984 to 2003. The key advantage of the SIPP is that it allows us to track the same individuals over several years. This allows us to estimate the rate of job transitions, as well as wage gains associated with those transitions.

Our empirical strategy is as follows. We first assume that wage changes for continuously employed workers reflect returns to experience. For workers who switch jobs, wage changes result from both experience accumulation and changes in the quality of the job match. Using these assumptions we estimate a baseline model that decomposes wage growth over this period into changes that arise from: experience accumulation; the returns to experience; the rate of job matching; and the returns to match quality. As our second specification, we augment the baseline model to also include a common time effect that affects all individuals' wages, regardless of experience or match quality. We then decompose the residual wage growth (net of this common component) into the key factors of interest. We identify the common effect using wage levels for new labor market entries. The results from both decompositions allow us to better understand the extent to which the temporal pattern of wage growth is driven by changes in experience accumulation and matching.

Our main finding that is that wage growth has varied considerably over the last 20 years. We find that the vast majority of the variation in wage growth is due to variability in the return to experience over time.[7] Although the return to experience seems to change from year to year, there is no strong evidence of a secular trend. On average over this time period, an additional year of experience increases wages about 4 percent but this gain varies from as much as 6 percent to as little as 2 percent. In contrast, essentially none of the changing pattern of wage growth can be attributed to changes in experience accumulation, job to job finding rates, or layoff rates. While these variables have the expected cyclical relationships, the overall magnitude of their contributions to changes in wage growth is extremely small. Therefore, we find that the return to experience is much more important than job matching for explaining the variability in early career wage growth. We know of no other work that has examined this question.

The extent to which the wage growth pattern varies with the business cycle depends crucially on our specification. In our base model (which does not account for common time effects), we find that the return to experience is strongly procyclical. In our second model (that does account for common time effects), we find that the cyclicality of returns to experience results fully from the wage level effects. That is, after we account for the common time effect, we find no remaining relationship between the returns to experience and the business cycle. We are unaware of any previous work that documents how the determinants of wage growth vary over the business cycle, let alone for any particular subgroup of the population.

We also estimate the model separately by skill groups and gender. While our estimates by subgroup are noisy, we find that average returns to experience and matching, and their cyclical and secular patterns, do not vary systematically by education or gender. Thus, we see no evidence that increasing differences in the return to experience and job matching across skill groups plays an important role in explaining rising wage inequality.

Our results suggest that policy makers should not be overly concerned that workers who enter the labor market during a recession will receive less wage growth over their first ten years than workers who enter during a boom. This suggests that the recent emphasis of policymakers to promote working among young low skilled workers is not misplaced. Furthermore, we find that for an average worker, experience accumulation is much more important than job matching in determining early career wage growth. Nonetheless, policies that are able to deliver especially high quality job matches may also be desirable.

Section 2 discusses the relationship between our results and previous work while Section 3 describes our methodological approach. We describe the data in Section 4 and the empirical results in Section 5. In Section 6 we summarize our main results and provide some conclusions.

2. Related Work

Although we are unaware of any previous study that has analyzed the changing pattern of lifecycle wage growth and its determinants, our research does intersect with a wide range of studies on related topics. There is a long literature in labor economics that has studied the age-earnings profile beginning with Jacob Mincer (1962) and Yoram Ben Porath (1967). These studies have shown that earnings increase rapidly early in the lifecycle (i.e., between ages 18 and 28) as workers invest in their human capital by gaining experience on the job.[8] In other words, they are more productive because they have more skills, and they are compensated accordingly.

A second literature has emphasized the importance of job matching in explaining lifecycle wage growth. Workers are able to find better matches for their skills over time. For example, since searching for a job is time consuming, an individual straight out of school may not wait until she finds the best match for her skills, but instead takes a job she can find quickly. Over time, however, she may find better matches for her skills. A substantial literature has arisen that examines the effects of job mobility (or job stability) on earnings using either regression analysis or structural modeling. Examples include Jacob Mincer and Boyan Jovanovic (1981), Christopher Flinn (1986), John Antel (1991), Pamela Loprest (1992), Robert Topel and Michael Ward (1992), Kenneth Wolpin (1992), Farber (1994), and Jacob Klerman and Lynn Karoly (1994). Theresa Devine and Nicholas Kiefer (1991) and Kenneth Wolpin (1995) provide surveys of different aspects of these literatures. These papers show that turnover is an important engine for wage growth.

Another strand of the literature has focused specifically on wage growth among low wage workers. Fredrik Andersson, Harry Holzer, and Julia Lane (2005) make use of a unique matched worker/firm data set to study job mobility for this particular group. They provide a very detailed analysis of worker mobility and wage progression demonstrating, among other things, the importance of turnover as a component of wage growth.

A number of papers have studied the relationship between the determinants of lifecycle wage growth and skill levels. Tricia Gladden and Christopher Taber (2000, 2004) focus on younger workers and compare the wage growth of medium skill workers with wage growth of low skill workers and find that they are similar. Helen Connolly and Peter Gottschalk (2000) look across all age groups of workers and find that more educated people receive higher returns to both tenure and experience. Since these papers use somewhat different concepts and different comparison groups they are not directly comparable.

Another related literature has examined how labor market transitions have changed over the business cycle. In a well known study, Steven Davis, John Haltiwanger, and Scott Schuh (1996) use plant level data and find that job destruction is strongly countercyclical in the manufacturing sector. In contrast, Eva Nagypal (2004) and Robert Shimer (2005) utilize individual level data on workers in all sectors of the economy and find that job separation rates are not countercyclical.[9] These authors also document that job finding rates and job to job transitions are highly pro-cyclical.

There is an extremely large literature on the cyclicality of aggregate wage *levels*. Katherine Abraham and John Haltiwanger (1995) provide a nice summary of the literature concluding that aggregate wages are slightly pro-cyclical, but have become more so in recent years. They also suggest that wages are pro-cyclical at the individual level, but that aggregate wages can mask this fact due to composition effects. This is because low wage workers, whose employment patterns are more pro-cyclical, constitute a larger fraction of the labor force in booms than in busts. This selection effect lowers average wages in booms.

A few papers have studied the effects of economic conditions early in one's career on earnings later in life. Paul Beaudry and John DiNardo (1991) are not interested in wage growth per se, but rather in contracting over the business cycle. They show that the lowest unemployment rate during an individual's tenure at a firm is a strong predictor of current wages. David Neumark (2002) examines the effects of job turnover on future wages. In doing so, he uses local labor market conditions when an individual is young as an instrument for turnover. He finds that job stability at young ages leads to higher earnings at older ages. Phil Oreopolous, Till von Wachter and Andrew Heisz (2006) find that there are large initial earnings losses from graduating college during a recession that dissipate after about 8 to 10 years. They find evidence of heterogeneous affects, for example, relatively lower skilled college graduates suffer larger and more permanent earnings losses.

3. Methodology

In this section we present our framework for modeling wage growth. Since previous research has shown that experience accumulation and job transitions are associated with wage growth, we model both labor market transitions and wage dynamics. We assume that time is discrete and denoted by t, which in practice will be monthly. Let j_{it} denote the job held by individual i at time t. To keep the notation simple we denote non-employment with a zero; so that $j_{it} = 0$ means that individual i was not working at time t. Therefore, for individuals who are working at time $t - 1$ (i.e. $j_{it-1} \neq 0$), there are three possible labor market transitions: stay on the same job, become non-employed, or switch to a new job. We write these three transition probabilities respectively as

$$\Pr(j_{it} = j_{it-1} | j_{it-1} \neq 0) \qquad (1)$$

$$\Pr(j_{it} = 0 \mid j_{it-1} \neq 0)$$

$$\Pr(j_{it} \neq j_{it-1}, j_{it} \neq 0 \mid j_{it-1} \neq 0).$$

Clearly these must sum to one.

Individuals who are not employed at time t - 1 start a new job with probability $\Pr(j_{it} \neq 0 \mid j_{it-1} = 0)$ and fail to start a new job with probability $\Pr(j_{it} = 0 \mid j_{it-1} = 0)$. Again, these two probabilities must sum to one.

Our primary focus is the relationship between labor market transitions and wage dynamics. Let ω_{it} denote the wage of individual i at time t. A key feature of our data (which will be discussed in the data section) is that we do not use wages from every month. As a result, the number of months between wage observations will vary across observations. With this in mind, define the ℓ^{th} period difference operator as Δ_ℓ, e.g. $\Delta_\ell \omega_{it} = \omega_{it} - \omega_{it-\ell}$. We consider two different empirical specifications for wage changes. In our first approach we assume that the structural (i.e., true) model[10] of wages is:

$$\Delta_\ell \omega_{it} = \beta_t \Delta_\ell \mathrm{A}_{it} + \Delta_\ell \eta_{ij_{it}} + \Delta_\ell \varepsilon_{it}, \qquad (2)$$

where A_{it} represents actual experience (and thus $\Delta_\ell \mathrm{A}_{it}$ is the amount of accumulated work experience between time periods $t - \ell$ and t), $\eta_{ij_{it}}$ is a match specific component between individual i and job j_{it}, and ε_{it} represents an error term which is orthogonal to the other components of the model. We assume that the quality of a match does not change unless an individual changes jobs so that for job stayers $\Delta_\ell \eta_{ij_{it}} = 0$ by assumption. We are also ignoring any effect from job tenure so that $\Delta_\ell \eta_{ij_{it}}$ may also include any effects from the loss of job tenure. Note that we assume that wage growth is linear in experience which is a reasonable approximation given that we only analyze young workers.

In our second specification we allow for a common wage level effect which affects all individuals' wages regardless of their experience or the quality of their job match. To motivate this specification suppose that wages are determined by the pricing equation

$$\omega_{it} = R_t H_{it}$$

where R_t is the rental rate of human capital at time t, and H_{it} is the amount of human capital for individual i at time t. Taking logs we define $\alpha_t = \log(R_t)$, which we refer to as the common time effect . We assume that $\Delta_\ell \log(H_{it}) = \gamma_t \Delta_\ell \mathrm{A}_{it} + \Delta_\ell \eta_{ij_{it}} + \Delta_\ell \varepsilon_{it}$, and re-define ω_{it} to be the log wage so that

$$\Delta_\ell \omega_{it} = \Delta_\ell \alpha_t + \gamma_t \Delta_\ell \mathrm{A}_{it} + \Delta_\ell \eta_{ij_{it}} + \Delta_\ell \varepsilon_{it} \,. \qquad (3)$$

In this framework, fluctuations in wage changes may be due to one of several factors. First, it may be that $\Delta_\ell \alpha_t$ changes over time, affecting everyone's wage, regardless of human capital level. For example, in Robert Hall's model (2005, this volume), $\Delta_\ell \alpha_t$ represents the growth rate of technological improvements or growth in the amount of capital used by each worker. Macroeconomists typically focus on α_t as the *sole* factor in explaining wage fluctuations (see Katherine Abraham, and John Haltiwanger, for example). This is a reasonable first approximation since for much of US history wage gains were shared by all skill groups. However, as Robert Hall points out, his model fails to account for many recent changes in the distribution of wages such as the well documented increase in wage dispersion. Moreover, as we pointed out in Section 2, there is ample evidence that other factors influence wage growth as well. These other factors are the focus of the paper.

A second explanation for shifts in wage growth is that the return to experience may change over time (that is to say, through β_t in equation (2) or γ_t in equation (3)). This might be the case if the rate at which individuals learn on the job varies over time, for example.[11] A third possibility is that changes in the amount of experience accumulation (that is to say, $\Delta_\ell A_i$) may result in changing wage growth. We generally would expect this component to be procylical because during recessions, individuals who are unemployed are not gaining work experience. Thus, one would expect this effect to lead overall wage growth to be higher during a boom.

A fourth factor in explaining variation in wage growth is changes in the quality of job matches over time (that is to say, $E(\Delta_\ell \eta_{ijit})$). We examine this empirically by looking at both job switchers that go directly from one job to another as well as job switchers who experience an intervening spell of unemployment. Direct job switches lead to changes in wage growth either because the rate of job switching changes or because the wage gains associated with each switch changes. As Robert Shimer (2004) and Eva Nagypal (2004) point out, job-to-job switching is pro-cyclical. Given that wages tend to rise with job-to-job transitions, increased job-to-job transitions will raise wages even if the average wage gain associated with these job changes does not change over time. Of course, it could also be the case that the average wage gain associated with job switching (the average change in the value of η_{ijit} given a job change) has changed over time. Similarly job changes involving an unemployment spell are likely to lead to negative wage growth either because those transitions (which typically involve wage losses) are countercyclical or because the amount of the wage losses are countercyclical.

When confronted with estimating equation (2) or (3), several identification issues arise. First, (as with all wage regressions) there is a selection issue because wage growth is only observed for workers who are employed in both periods. We assume that sample selection is based on an individual fixed effect, which is differenced out, but that there is no selection on $\Delta_\ell \varepsilon_{it}$. That is, we allow individuals with permanently low productivity to have different participation rates than those with permanently high productivity. However, we do not allow short term wage fluctuations from changes in ε_{it} to affect the decision to work.

A second problem lies in estimating the returns to experience (β_t in equation (2) or γ_t in equation (3)). For many reasons we would expect job matches ($\eta_{ij_{it}}$) to be correlated with experience (A_{it}). For example, a worker who has been unemployed for an extended period of time may become less choosy about jobs, and will accept a worse match. This is problematic because it is very difficult to measure match quality.[12] As a result, running a regression of wage growth on the change in experience without including match quality will not yield a consistent estimate of the returns to experience. Instead we use an alternative approach where we utilize only the sample of workers who do not switch jobs (stayers) so that $\Delta_\ell \eta_{ij_{it}} = 0$. Under model (2), one can write

$$E\left(\frac{\Delta_\ell \omega_{it}}{\Delta_\ell \mathrm{A}_{it}} \mid \Delta_\ell j_{it} = 0\right) = E\left(\frac{\beta_t \Delta_\ell \mathrm{A}_{it} + \Delta_\ell \varepsilon_{it}}{\Delta_\ell \mathrm{A}_{it}} \mid \Delta_\ell j_{it} = 0\right) \qquad (4)$$

$$= \beta_t$$

where $E\left(\frac{\Delta_\ell \varepsilon_{it}}{\Delta_\ell \mathrm{A}_{it}} \mid \Delta_\ell j_{it} = 0\right) = 0$ by assumption. Thus, in principle, we can estimate β_t consistently by simply taking the sample mean of $\frac{\Delta_\ell \omega_{it}}{\Delta_\ell \mathrm{A}_{it}}$ for stayers in each month. Since the sample sizes are too small to estimate this parameter month by month, we smooth across months using kernel regression.

Separately identifying the change in the common time effect ($\Delta_\ell \alpha_t$) from the return to experience (γ_t) in model (3) is not straight forward. The problem is that for continuously employed workers, if we measure wage changes over a fixed time period, say 4 months, there is no variation across this group in the amount of experience accumulated ($\Delta_\ell \mathrm{A}_{it}$). As a result it is impossible to separately identify these two components using wage changes on stayers as we did in equation (4).[13] One approach would be to use movers with spells of non-employment to try to separately identify these parameters. However, as we pointed out previously the change in experience is likely to be correlated with the change in match quality which we are unable to measure very well. Therefore, in order to obtain consistent estimates of the parameters of the model, we take an alternative approach. First, we estimate α_t , the common time component to wages, using the wages of new labor market entrants because they all have zero experience.

Assuming that the quality of new workers, θ_i (where θ_i is discussed more formally in endnote 8), and the quality of new matches does not change over time, changes in the wages of new entrants change only because of changes in α_t. That is we assume that we can write expected wages of new entrants as

$$\begin{aligned} \mathrm{E}[\omega_{it} \mid \mathrm{A}_{it} = 0] &= \alpha_t + \mathrm{E}[\theta_i + \eta_{ij_{it}} + \varepsilon_{it} \mid \mathrm{A}_{it} = 0] \\ &= \alpha_t + \textit{a constant.} \end{aligned}$$

Because wages of new entrants are equal to α_t (plus a constant that can be differenced away), changes in average wages of entrants yield consistent estimates of $\Delta_\ell \alpha_t$. We use monthly data to estimate α_t and smooth as above with kernel regression. For this estimation procedure we use the larger CPS sample rather than SIPP in order to obtain more precise estimates.

In the second stage, now that we have estimated α_t, we use a strategy for estimating γ_t that is analogous to (3).

$$\begin{aligned} \mathrm{E}\Big(\frac{\Delta_\ell \omega_{it} - \Delta_\ell \hat{\alpha}_t}{\Delta_\ell \mathrm{A}_{it}} \mid \Delta_\ell j_{it} = 0\Big) &= \mathrm{E}\Big(\frac{\gamma_t \Delta_\ell \mathrm{A}_{it} + \Delta_\ell \varepsilon_{it}}{\Delta_\ell \mathrm{A}_{it}} \mid \Delta_\ell j_{it} = 0\Big) \qquad (5) \\ &= \gamma_t . \end{aligned}$$

Here we take the sample mean of $\frac{\Delta_\ell \omega_{it} - \Delta_\ell \hat{\alpha}_t}{\Delta_\ell \mathrm{A}_{it}}$ smoothing with kernel regression. Compared to our estimation of the first model that does not account for a possible common time effect, we have simply taken our estimates of wage growth and first subtracted out our estimates of changes in the common component of wages before applying our statistical procedure.

We should point out some problems that arise with our approach to estimating α_t. The fundamental problem is that the value of the unobserved components of workers' wages ($\theta_i + \eta_{ij_{it}} + \varepsilon_{it}$) may change across new entrant cohorts for one of several reasons. For example, it could be that the average individual fixed effect (θ_i) changes from cohort to cohort, because of changes in the quality of education. A second, and likely more serious issue, is sample selection bias. To be in included in our sample, an 18 year old must be working and not in school. However, there have been both secular and cyclical changes in labor force participation rates and college attendance rates of young individuals. Most notably, labor force participation rates for 18 year olds have been falling over our sample period.

Since we do not believe that it is possible to perfectly separate changes in the common aggregate component from the returns to experience, we present results using models both with and without our estimates of α_t and allow the reader to choose their preferred specification. One can interpret the estimates without α_t as incorporating both time and experience effects. The results with α_t try to separate these two processes, although this separation is not as clean as one might like. We show below that many of our main results are qualitatively unaffected by the assumptions used to obtain $\Delta_\ell \alpha_t$. However, we find one very important difference which is that experience growth is strongly procyclical in the first specification, but this procyclicality disappears when we control for $\Delta_\ell \alpha_t$.

Our next goal is to summarize the importance of changes in job matches on wage growth. Since it is very difficult to measure changes in match quality ($\Delta_\ell \eta_{ij_{it}}$), as we pointed out earlier, we simply estimate the expected wage gains for two types of switchers: job to job switchers and job-to-nonemployment to job switchers. For brevity, we describe our methodological approach for our second model where we do not include α_t. Define $\mathrm{N}_{it\ell}$ to be an indicator of whether person *i* experienced a nonemployment spell between periods $t-\ell$ and t. For a job to nonemployment to job switcher, the average wage gain at switching is

$$\mathrm{E}(\Delta_\ell \eta_{ij_{it}} \mid j_{it} \neq j_{it-\ell}, \mathrm{N}_{it\ell}=1) = \mathrm{E}(\Delta_\ell \omega_{it} - \hat{\gamma}_t \Delta_\ell \mathrm{A}_{it} \mid j_{it} \neq j_{it-\ell}, \mathrm{N}_{it\ell}=1), \qquad (6)$$

where the expectation is over all possible durations of non-employment. We estimate this just by taking the sample mean of ($\Delta_\ell \omega_{it} - \hat{\gamma}_t \Delta_\ell \mathrm{A}_{it}$) for job to non-employment to job switchers in each month (using kernels to smooth). Basically, we take wage growth in each period for this sample and subtract out our estimates of the change in the common time component (estimated earlier) and also subtract out the change in wages due to experience. Similarly we can identify the average wage gain at switching for job to job switchers using

$$\mathrm{E}(\Delta_\ell \eta_{ij_{it}} \mid j_{it} \neq j_{it-l}, \mathrm{N}_{it\ell}=0) = \mathrm{E}(\Delta_\ell \omega_{it} - \hat{\gamma}_t \Delta_\ell \mathrm{A}_{it} \mid j_{it} \neq j_{it-\ell}, \mathrm{N}_{it\ell}=0). \quad (7)$$

In words this is the average wage gain that occurs at job to job switches. We estimate this in a manner analogous to the job to non-employment to job switchers.

Given our estimates of the various sources of wage growth, our next goal is to decompose overall wage growth into its various components using Oaxaca style decomposition. We describe the decomposition for the first model in which we do not incorporate α_t. The extension to the model including α_t is straightforward in that we just perform the same decomposition of wage growth net of changes in aggregate wage levels (i.e. we decompose $E(\Delta_1 \log(H_{it})) = E(\Delta_1\omega_{it} - \Delta_1\alpha_t)$ rather than $\mathrm{E}[\Delta_1\omega_{it}]$). One issue that arises in this type of decomposition is the definition of wage growth among workers who are not working. To keep the model as simple as possible, for a worker who is not working, we define their implicit wage (or match component) as their wage (or match component) on their previous job. Thus wage growth is 0 by definition for a non-employed worker, but is nonzero when they start their new job. We also note that wage growth at time *t* is well defined only for individuals who worked at some point prior to *t*. We leave this conditioning implicit as every expectation we write below conditions on individuals who worked at some point prior to time *t*. Under this normalization we can write

$$\begin{aligned}\mathrm{E}(\Delta_1\omega_{it}) = {} & \beta_t\mathrm{E}(\Delta_1\mathrm{A}_{it}) + \mathrm{E}(\Delta_1\eta_{ij_{it}} \mid j_{it} \neq 0, j_{it-1} = 0)\Pr(j_{it} \neq 0, j_{it-1} = 0) \\ & + \mathrm{E}(\Delta_1\eta_{ij_{it}} \mid j_{it} \neq j_{it-1}, j_{it-1} \neq 0)\Pr(j_{it} \neq j_{it-1}, j_{it-1} \neq 0)\end{aligned}$$

The first component is the wage growth due to experience gained on the job, the second represents the change (likely negative) associated with job to non-employment to job changes, and the third represents the wage gains that occur at job to job transitions. Since our SIPP panels are relatively short (2 to 4 years) and since durations of non-employment can sometimes be very long, we estimate the three transition rates described in equation (1) and use these to simulate the probability of a job to non-employment to job transition.[14]

It is easiest to explain the decomposition this if we stack the parameters and write this in vector notation:

$$G_t = \begin{bmatrix} \beta_t \\ \mathrm{E}(\Delta_1 \eta_{ij_{it}} \mid j_{it} \neq 0, j_{it-1} = 0) \\ \mathrm{E}(\Delta_1 \eta_{ij_{it}} \mid j_{it} \neq j_{it-1}, j_{it-1} \neq 0) \end{bmatrix}, \mathrm{X}_t = \begin{bmatrix} \mathrm{E}(\Delta_1 \mathrm{A}_{it}) \\ \Pr(j_{it} \neq 0, j_{it-1} = 0) \\ \Pr(j_{it} \neq j_{it-1}, j_{it-1} \neq 0) \end{bmatrix} \quad (8)$$

We denote the mean of parameters over years as

$$\overline{\mathrm{X}} \equiv \frac{1}{\mathrm{T}} \sum_{t=1}^{\mathrm{T}} \mathrm{X}_t \, .$$

The advantage of this additional notation is that it allows us to express the decomposition in the following way

$$\mathrm{E}(\Delta_1 \omega_{it}) = G'_t \mathrm{X}_t \qquad (9)$$

$$= G'_t \overline{\mathrm{X}} + G'_t(\mathrm{X}_t - \overline{\mathrm{X}}) \, .$$

The first part of this decomposition $G'_t \overline{\mathrm{X}}$ reflects how much of the wage change can be explained purely by changes in the coefficients over time. The remaining component contains the amount left which is due to labor market transitions changing over time.

We decompose the result even further. In each year the value of $G'_t \overline{\mathrm{X}}$ is a sum of three separate components (associated with change in experience, number of job to job transitions, and number of job to non-employment to job transitions). We present each of these three components later in the chapter.

We estimate the regressions above and perform the decompositions above allowing the coefficients to vary over time and across various demographic groups.

We should point out here that this decomposition should be interpreted as descriptive. Separating the returns to tenure from the returns to experience and dealing with the many sample selection problems inherent with turnover and labor supply among low wage workers is beyond the scope of this work. Our Results should be interpreted as a statistical decomposition of the observed wage growth in the data rather than causal effects.

4. Data

For our main analysis, we use pooled data from the Census Bureau's Survey of Income and Program Participation (SIPP). The SIPP surveys are a series of two to four year panels that began in 1984. The SIPP panels from 1984 through 1993 consist of a national sample of around 20,000 households. The 1996 and 2001 SIPP panels include close to 40,000 households. Combining all of the SIPP panels we have information on all years from 1984 to 2003 except for 2000. The SIPP interviews households every four months and collects detailed labor market information on all individuals in the household over the previous four months. Each interview is referred to as a wave. A key aspect of the of the SIPP for our analysis is that the survey identifies up to two different employers for each individual in each wave and these job identifiers are consistent across waves.[15] As a result we are able to identify cases where individuals transition by month from: non-employment into work; work into non-employment; stay in the same job; or, switch employers.[16]

The SIPP also provides direct data on hourly wages for workers who are paid by the hour. For salaried workers, we calculate hourly wages for each employer by dividing monthly earnings by usual hours per week worked times weeks worked in the month.[17] This allows us to calculate wage changes associated with labor market transitions. Hourly wages are deflated to 2003 dollars using the monthly CPI price index and we drop individuals whose wages are ever below $1. Since the focus of our analysis is on wage growth early in the career, we confine our sample to individuals between the ages of 18 and 28 who are never enrolled in school during the time they are in the SIPP. We divide the sample into 3 educational groups: those who have not completed high school (drop-outs), high school graduate (but no college), and some college (or more). Our main sample includes over 900,000 person-month observations. It is worth noting that the time series patterns of unemployment and annual wage growth in the SIPP closely tracks that found in the CPS.

The fact that the SIPP collects new data every four months is clearly advantageous compared to annual surveys that suffer from greater recall bias. On the other hand, it is well known that for many variables, respondents do not accurately report changes that occur each month. Instead changes tend to be clumped at the seam between the last month of a previous interview and the first month of the next interview. Because of this "seam bias" we only use one wage observation on each interview wave for workers who are continuously employed with the same firm. Thus for workers who stay on the same job we construct our wage change measure as $\omega_{it} - \omega_{it-\ell}$ where ℓ is four (months). We then use the number of weeks worked in the interval as our measure of $[A_{it} - A_{it-\ell}]$.

When a worker works on two different jobs between interviews, we record two wages for that wave and use both in constructing our wage differential. So for example, suppose a worker was interviewed in April (call this $t = 4$). In July they switched to a new job and then were interviewed again in August. We would gather two wages from the August interview. The wage during the last month (June) on the old job and the wage from the current job (in August). We then obtain two wage changes in this wave for the person. First we would take their wage from the last month working at their old job (June which corresponds to $t = 6$) and subtract the wage from the previous wave $\omega_6 - \omega_4$. The person would be recorded as a stayer in this case because they hadn't switched employers yet. For the second wage observation we would use the wage from the interview month (August) and subtract the previous wage (June) to form $\omega_8 - \omega_6$. This observation would correspond to a job-to-job transition since the person was working a different job in August than June and was continuously employed. As a result, job changers are over represented in our sample of wage changes. However, this will not bias our results as we condition on job changing in the empirical work. Note that given the manner in which the data is constructed, we will never observe more than one job change in a period in which we obtain wage differentials.

5. Results

In the introduction we showed that wages of low skilled young workers grow about 4.5 percent per year. Using estimates from our two models of wage growth, this section presents evidence on the sources of that wage growth.

Returns to Experience Accumulation and Job Changes

First, we present parameter estimates from equation (2), which does not include the common time effect α_t. The parameters represent the returns to experience (i.e., the average wage change associated with an extra year of work for stayers), the returns to job to job switches (i.e., the average wage change associated with a job switch) and the returns to job changes with an intervening non-employment spell. These are graphed in the top panel of Figure 3a for the combined group consisting of high school graduates and drop-outs. The returns to experience, β_t, depicted with a solid line, vary considerably over this period but average about 4 percent. The other two lines, representing the wage gains associated with job to job transitions (dashed line), and job to non-employment to job transitions (vertical lines), also vary over time. On average, wages rise about 3 percent during job to job switches and decline about 3 percent during job switches with an intervening non-employment spell.

These results are similar in magnitude to those found by Helen Connolly and Peter Gottschalk (2000) who include older workers and also use the SIPP pooling data over the 1986-1993 period. For example, for workers with high school or less they find that wage gains at job to job changes are around 3.5 percent and that wage losses are just under 3 percent for job to non-employment to job transitions. Our estimates of the wage losses associated with job to non-employment to job transitions are smaller than Farber's (2005) estimates of the wage losses associated with job loss using the Displaced Worker's Survey, but show similar time trends. Farber (2005) finds that earnings losses of displaced workers (including foregone earnings growth from not having a job) declined from 13% in the 1980s to 10% in the early 1990s to 8% in the late 1990s, then increased to 17% in the early 2000s.[18]

In the bottom panel of Figure 3a we present results that account for changes in the common time effect on wage levels using the model described in equation (3). The bottom panel of 3a is analogous to the top except that we also include our estimate of $\Delta_1\alpha_t$ (that is, the change in the common time effect, at an annualized rate) as the solid line with + marks. Clearly, including α_t does make some difference in the results although the overall patterns do not differ dramatically. For example, the returns to experience continue to show considerable variation over time. However, one can see that the pattern of the returns to experience is distinctly less procyclical in the bottom panel than in the top. Most notably a dip in the returns to experience in 1992 just after the 1990-91 recession is clearly visible in the top pattern but disappears in the bottom.

In the first two rows of Table 1 we formally test whether the time patterns apparent in the figures are statistically significant by performing Wald tests for whether the parameter values are constant across all months of the data.[19] The columns refer to the parameter being tested and the rows refer to whether the model contains the common time effect. The table entries show the *p*-values from the Wald tests. Whether or not we include the common time effect, we strongly reject the null hypothesis that the return to experience is constant over time. We also reject the null that the return to job to job switches is constant over time. However, despite the notable movements shown in Figure 3a, we actually do not reject that the job to non-employment to job return is constant, although the *p*-value in the second model is 0.0518 which is very close to a marginal rejection of constancy.

In Table 2, we test the cyclicality of the parameter values by taking each of the time series of monthly estimates and regressing them on a constant, a time trend, and the monthly unemployment rate. The entries in the table show the coefficient on the unemployment rate and standard error from the regression. In our model without the common time effect, we find that the return to experience is highly pro-cyclical. A one percent increase in the unemployment rate is associated with a one percent annual decline in the return to experience. This result is highly significant. The coefficients on job to job and job to non-employment to job rates are both procyclical: a one percent increase in the unemployment rate is associated with a half point percent decline in wage growth for both job to job and job to non-employment to job switchers. However, the pro-cyclical patterns for job switchers are not statistically significant.

When we include the common time effect, which is strongly cyclical, we find that even the return to experience is not cyclical. This is not purely due to an increase in standard errors. The point estimate on cyclicality for the returns to schooling in Table 2 falls from -0.0113 to -0.0003 after we control for $\Delta_\ell \alpha_t$.

The results strongly suggest that the pro-cyclicality of β_t was due to pro-cyclicality associated with common component to wage levels rather than in the returns to experience. Interpreting this in terms of the economics framework in the methodological section, this suggests that the human capital rental rate appears to be procyclical while the human capital production function is not. When interpreted in this way, this result seems quite reasonable, the demand for human capital rises during a boom due to increased productivity. This suggests that this component is actually a transitory component of wage levels rather than permanent wage growth. We view this as an important finding. Because of the problems with this specification discussed in Section 3, results from this specification should be taken with some caution. However, the fact that including this variable in the regression makes such a difference suggests that at the very least it is not simply noise.

In Figure 3b we show the parameter estimates when we estimate the model separately by education groups. Figure 3c shows parameter estimates for men and women. Both figures refer to results from the first model without α_t (that is to say, equation 2). The top left panel of Figures 3b and 3c show the estimated return to experience. Although there is a lot of variability in these series, both across time and across demographic groups, there is no strong secular change in the return to experience. Looking at the top left panel of Figure 3b, it appears as if the trends in return to experience may differ by education groups with larger trends for the more educated. We examined this more in depth. While the point estimates do suggest stronger trends for the more educated, the standard errors are large enough that one can not say much about this trend with confidence. Furthermore, for all demographic groups (except college), the return to experience is about 4 percent. In other words, an additional year of experience, holding all else constant, increases wages by about 4 percent. The return to experience for college graduates is about 5 percent. The top right and bottom left panels of Figures 3b and 3c also show the average wage change associated with a job to job change and a job to non-employment to job change, respectively.

The most dramatic difference across groups is that the coefficients for dropouts are particularly pro-cyclical —both the return to experience and the return to job to non employment to job changes appear to be more pro-cyclical than for other groups.

When we account for the common time effect α_t, results are very similar to the results in Figures 3b and 3c, so we do not present those results. Accounting for α_t slightly reduces the estimated return to experience for high school graduates and drop-outs (although it is still estimated at over 3% for both groups). Also, the estimated fall in the return to experience for college graduates and high school graduates largely vanishes. As in figure 3a, the return to experience appears to be less procyclical after accounting for the common time effect, although due to the noisier results the pattern is less transparent.

To summarize, all three of the returns to labor market transitions vary considerably over time and all exhibit some pro-cyclicality. However, only the return to experience is related to the business cycle in a statistically significant fashion. Once we control for the common time effect, however, the return to experience is no longer pro-cyclical.

Patterns in Labor Market Transitions

In the previous section we examined how the *returns* to labor market transitions changed over time and examined the cyclical properties of our parameter estimates. However, wage growth can also vary over time because of changes in the rates of these transitions irrespective of their returns. For example, more people are working and accumulating experience during booms. With that goal in mind we now document trends in labor market transitions over the last 20 years. Recall that we examine three types of labor market transitions in our model: staying on the same job, job to job transitions and job to non-employment to job transitions. Also recall that because the SIPP panels are short, we cannot directly observe all job to non-employment to job transitions, as we do not know if individuals moving from non-employment to employment were ever previously employed. Therefore, in order to measure these transition rates with our SIPP data, we estimate the three transition probabilities described in section 3: employment to non-employment, non-employment to employment, and job to job. We then use these transition probabilities to simulate the labor market transitions for our model. Clearly, the job to job transition rate is directly related to the probability of a job to job switch. However, the job to non-employment to job switches depend on two transition probabilities, the transition into non-employment and then the subsequent transition to employment. Experience accumulation also depends on both the job to non-employment rate and the non-employment to employment rate.

We calculate the underlying transition rates that determine our labor market transitions annually, for the combined group of dropouts and high school graduates. These are shown in Figure 4a. The patterns show considerable variability over time. These movements are strongly statistically significant as can be seen in the bottom row of Table 1 where we show that we strongly reject that the transition rates are constant over time. In the bottom row of Table 2 we also find that these rates are all closely related to the business cycle (in the direction that one would expect). As we mentioned earlier, this is also consistent with the findings of Eva Nagypal (2004) and Robert Shimer (2005).

We present the transition rates by education group in Figure 4b and by gender in Figure 4c. The results are fairly similar across groups with a few notable exceptions. Non-employment to employment transition rates are higher for men and for more educated workers. Employment to non-employment transition rates are lower for men and for more educated workers. Therefore, the higher employment rates of men and the educated are the result of both higher non-employment to employment transition rates and lower employment to non-employment transition rates. Furthermore, non-employment to employment transitions for less educated workers are more pro-cyclical than for more educated workers. Another notable difference is a much stronger decline in job to job transitions for high school dropouts than for the other education groups.

While all three transition rates appear to be trending downward somewhat, all three are highly cyclical as one would expect. The job to job rate and the non-employment to job rate are highly pro-cyclical while the job to non-employment rate is countercyclical.

We use the estimated transition rates and the simulation model to calculate the probability that someone is employed, making a job to change, or a job to non-employment to job change for each month during our sample period. For the most part, results from the model are unsurprising, so we do not show graphs of the results. The employment rate, which we use for measuring the amount of accumulated experience, is pro-cyclical. For our base sample of high school graduates and drop-outs, the employment rate rises from 69% in 1984 to 73% in 1989, declines to 69% in 1993, rises to 75% in 1999, then declines back to 70% in 2003. These participation rates line up closely with values from the CPS.[20] The job to non-employment to job rate is slightly pro-cyclical, falling from 2.1% per month in the mid-1980s to 1.5% in 1992, rising to 1.7% in 1996, falling to 1.5% in 1999, then rising to 1.7% in 2003. Recall that the job to non-employment to job rate is a function of the job to non-employment rate (which is countercyclical) and the non-employment to job rate (which is pro-cyclical), so the resulting series is somewhat acyclical. Lastly, the simulated job to job transition rate unsurprisingly looks like the estimated job to job transition rate.

Decomposing Changes in Wage Growth Over Time

Thus far we have shown that there have been substantial changes over time in labor market transition rates and in the wage changes associated with these transitions. In this section we decompose overall wage growth into its various components using the Oaxaca decomposition approach described in equation (9). This method basically attempts to ask the following question: what would the time series of wage growth look like if we simply held the transition rates constant at their average value over the whole time period so that all wage growth was only due to the changing returns? The result of this experiment would give us a sense of how much of the observed pattern of wage growth was due to changes in transition rates versus changes in returns.

In Figure 5 we graph the results of the decomposition described in equation (9) converting our monthly estimates into annual units. The top panel presents the decomposition of the change in wage growth over time ($E[\Delta_1 \omega_{it}]$) while the bottom panel presents the decomposition of wage changes net of the common time component ($E[\Delta_1 \omega_{it} - \Delta_1 \alpha_t]$). In both panels the solid line represents the overall predicted wage growth ($G'_t X_t$). The dashed line presents the component that only allows the coefficients (returns) to change $G'_t\overline{X}$ while the dotted line presents the remainder term ($G'_t(X_t - \overline{X})$). Clearly the dashed line explains virtually all of the change in the lifecycle wage growth. This result is also robust across subgroups (not shown). In short, changes in the coefficients explain almost all of the variability in wages, and changes in the transition rates explain essentially none of it.

Another perhaps surprising aspect of this is that we do not find that trends in the amount of labor force experience (due to labor supply) are important. We looked at this more closely for both men and women. For this sample there is essentially no trend in labor force experience for either of these groups.

We find this result extremely surprising. As expected experience and job to job transitions are associated with wage gains while non-employment spells are associated with wage losses. Also, as expected, job to job and job finding rates are highly pro-cyclical while job to non-employment rates are counter cyclical. However, the magnitude of these effects in explaining the variation in overall wage growth is miniscule as is clearly evident in Figure 5.

We next decompose the dashed line in Figure 5 ($G'_t\overline{X}$) into its various parts: a component related to the return to experience, a component related to job to job switches, and a component related to job to unemployment to job switches. We show this for both of our wage growth models in the two panels in Figure 6. The solid line in each panel reproduces the value of $G'_t\overline{X}$ from Figure 5. We then present the three different components that contribute to it. Very clearly, the coefficient on experience is chiefly responsible for the main result. In short, the great majority of the variability in wage growth over time comes from one source: variability in the returns to experience.

Another interesting finding is also apparent in Figure 6. While the level of wage growth is entirely accounted for by the return to experience, job to job transitions lead to positive effects while job to non-employment to job transitions lead to negative effects and these two roughly offset each other. In most years wage growth associated with job changes accounts for less than 10% of wage growth. Thus, we find that job changes are less important for understanding early career wage growth than does Robert Topel and Michael Ward (1992), who find 30% of early career wage growth occurs at job to job transitions. Gadi Barlevy (2005) finds that job to job transitions are more important for wage growth than what we find, but are less important for wage growth than what Robert Topel and Michael Ward find. Further research is necessary to better understand whether differences in results are attributable to differences in data (ours is more recent and for less educated workers), or differences in methodology.

Ideally, we would like to understand why the return to experience has changed over time but unfortunately we see no obvious explanation. We leave further exploration of this result to future research.

6. Conclusions

This chapter analyzes the changing patterns of early career wage growth for less skilled workers over the last twenty years. We find that wage progression has varied considerably over this period. Wage growth for young individuals averaged about 4.5 percent over this period ranging from as high as 6 percent to as low as 3 percent.

We develop a model of wage changes in order to identify the key determinants of lifecycle wage growth for younger workers and how these factors have influenced the changing pattern of wage growth. In our first specification, in which we do not attempt to account for the common time effect on wages shared by all workers, we find that the returns to experience are highly variable and pro-cyclical. In our second specification which incorporates a common time effect, we find no relationship between the return to experience and the business cycle. Instead, we find that most of the pro-cyclicality of wage growth comes from the common time effect. Nevertheless, even in this second model the returns to experience still exhibits a fair degree of variation over time.

Because our strategy for identifying the common time effect is problematic, we cannot be sure if it is the common time effect or the return to experience that causes the procyclicality of wages during our sample period. To the extent that it is the common time effect that is responsible for the pro-cyclicality in wages, the results are straightforward to interpret. Improvements in technology and increases in the amount of capital per worker imply that the productivity of all workers increases, regardless of experience level. This makes it a good time to hire, even if wages of workers are being bid up. Thus, wages of continuing workers rises.

We then examine wage gains associated with different labor market transitions in order to identify the relative importance of wage growth on the job (which we interpret as the return to experience, plus, potentially a common time component) and wage growth when moving across jobs (which we interpret as the change in job match quality). Surprisingly we find that virtually all of the change in wage growth over time is accounted for by wage growth on the job. Although we do find that experience accumulation and job changes are related to the business cycle, the magnitude of the contributions to overall wage growth from these sources is negligible.

Although there is variability in the return to experience, it has averaged a healthy 4 percent over our sample period and generally speaking, does not vary much by gender or education level. The fact that the returns to experience have moved in ways unrelated to the business cycle is an interesting finding that deserves more attention. We do not have any obvious explanation of this result and thus are hesitant to make policy prescriptions based on this finding. Future research both to confirm our results and to delve deeper into this issue is clearly needed.

Taken as a whole, our results suggest that the business cycle plays a surprisingly small role in lifecycle wage growth and that policymakers should not be overly concerned that workers who enter the labor market during recessions will suffer slower wage growth over their careers. While it is true that workers who are in the labor market during a downturn will experience longer unemployment spells and fewer job to job transitions, this will have relatively little effect on wage growth over the first ten years of the career. Overall, our results suggests that experience accumulation is potentially an important pathway out of poverty and so attempts by policymakers to encourage work do not seem to be misplaced. In contrast, we do not find job switching to be an important explanation for early career wage growth, at least on average. Nonetheless, policies that produce particularly high quality matches may still be desirable.

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Table 1: Tests of the constancy of parameter estimates and transition rates

p-values on Parameters from Wage Growth Model			
	Coefficient on Experience	Coefficient on Job to Job Transitions	Coefficient on Job to Non-employment to Job Transitions
Model without α	0.003	0.035	0.227
Model with α	0.000	0.005	0.052
p-values on Labor Market Transition Rates			
	Job to Job	Job to Non-employment	Non-employment to Job
	0.0000	0.0000	0.0000
Note: Table entries show the probability values for the null hypothesis of parameter constancy over time against the alternative of time varying parameters			

Table 2: Tests of the cyclicality of parameter estimates and transition rates

Regression of Parameters from Wage Growth Model on Unemployment Rate			
	Coefficient on Experience	Change in Wage at Job to Job Transitions	Change in Wage at Job to Non-employment to Job Transitions
Model without α	-0.0113 (0.0033)*	-0.0051 (0.0055)	-0.0055 (0.0069)
Model with α	-0.0003 (0.0079)	-0.0053 (0.0055)	-0.0018 (0.0061)
Regression of Job Transition Probabilities on Unemployment Rate			
	Job to Job	Job to Non-employment	Non-employment to Job
	-0.0024 (0.0006)*	0.0015 (0.0006)*	-0.0064 (0.0015)*
Notes: Table entries show the results of regressions on the monthly unemployment rate. Newey-West standard errors in parentheses * Statistically significant at the 5% level			

Endnotes

[1] We thank Dan Aaronson for his help with the CPS data and Phil Doctor for excellent research assistance. We thank the editors, Peter Gottschalk, and two anonymous referees for comments.
[2] For example, wages of high school drop-outs aged 18-28 fell from about $12 an hour 1979 (in 2004 dollars) to under $10 an hour in 2004.
[3] We constructed this profile using the 1996 SIPP panel. We regressed log wages on age dummies and calendar year dummies for high school graduate and high school dropout men. We then present the predicted value from this regression in 1996 looking across ages. The profile, then, should be interpreted as the wages of individuals of different ages in a single year.
[4] It is important to distinguish our discussion of *changes* in wages for individuals from the extensive literature on the cyclicality of aggregate wage *levels*.
[5] Specifically, we estimate the percent increase in the hourly wage for individuals who were working in the survey wave, and were also working in the previous Outgoing Rotation Group 12 months prior.
[6] Note that sample members in Figure 2 age one year between the two time periods we observe them. In other words, we are measuring wage growth between ages 18 and 19, 19 and 20, and so on for the same people between adjacent years. Furthermore, Figure 1 shows that wages increase rapidly with age. So although there has been little aggregate change in wage levels for low skilled workers over this time period, the wages of continuously employed young workers grow as they age.
[7] In the augmented model that accounts for the common component to wages, we find that this component explains a large portion of wage growth. This is not surprising given previous work on the changing wage structure and the variation in wages across the business cycle. Nonetheless, wage growth *net* of this component, is virtually entirely explained by changes in the return to experience.
[8] James Heckman, Lance Lochner, and Christopher Taber (1998) provide a more recent version of this basic model.
[9] Robert Shimer (2005) claims that the differences come from two sources. First, Steven Davis, John Haltiwanger, and Scott Schuh (1996) use manufacturing sector data, which may not be representative of the economy as a whole. Second, they use plant level data instead of individual level data. A plant can destroy jobs by merely not hiring new workers. If firms quit hiring new workers during a recession, jobs will be destroyed as workers quit (although the job separation rate may not necessarily rise), but the hiring rate will fall. Therefore, a countercyclical job destruction rate is consistent with an acyclical job separation rate.
[10] Equation (2) can be derived from the following model of wage levels:

$$\omega_{it} = \theta_i + \sum_{s=0}^{t} \beta_s (\mathrm{A}_{is} - \mathrm{A}_{is-1}) + \eta_{ij_{it}} + \varepsilon_{it}$$

where θ_i is an individual specific fixed effect that is potentially correlated with experience A_{is} and match quality $\eta_{ij_{it}}$. First differencing this equation and assuming that β_s changes sufficiently slowly that $\beta_t \approx \beta_{t-\ell}$ yields equation (2).
[11] In a standard human capital model one would expect the returns to experience to be countercyclical as the cost of investing in human capital is lower during a recession.
[12] See Tricia Gladden and Christopher Taber (2006) for an attempt to measure the distribution of $\eta_{ij_{it}}$.
[13] This is essentially an example of the fundamental problem of separating time, age, and cohort effects. For stayers age, time, and experience are perfectly collinear.
[14] For details on the simulation please see the working paper version of this study available at www.faculty.econ.northwestern.edu/faculty/taber.
[15] In the CPS, job to job transitions can only be identified beginning in 1994 (Bruce Fallick and Charles Fleischman, 2001).
[16] For the 1996 and 2001 SIPPs job changes are only identified across waves.
[17] The fact that some months contain 5 weeks rather than 4 sometimes leads to spurious wage changes within a wave. For these cases we use 4.3 weeks rather than the actual weeks to calculate the wage. In the 1996 and 2001 SIPP panels we do not know weeks worked in a month by employer. Adjusting the pre-1996 SIPP data to correspond to this measure of weeks has almost no effect on our results.
[18] We should point out that Farber estimates the earnings loss associated with being a displaced worker, whereas our measure is the wage loss for job to non-employment to job transitions. The associated job loss may be voluntary, or the job loss may be for cause. Furthermore, we measure wages whereas Farber measures earnings. Lastly, we measure wage losses for a younger group of workers, who have not had the time to find good matches and have not

had time to gain firm-specific human capital. Nevertheless, we both find that earnings losses associated with job loss diminished in size during the 1990s.

[19] Since we are using a kernel smoother to present the results in the figures, this can make parameter estimates appear more stable over time than the actually are. Because we are using a two stage procedure to estimate the mean wage changes for movers, calculation of standard errors is not straight forward since one must correct for the first stage estimation of β_t. We allow for this estimation error by treating the full model as one large GMM system and then perform Wald tests for constancy of parameter values across all months.

[20] Employment rates in the CPS tend to be about 2% lower than in our simulated data in every year. However, this difference does not change over time, so both series show almost identical cyclical fluctuations.

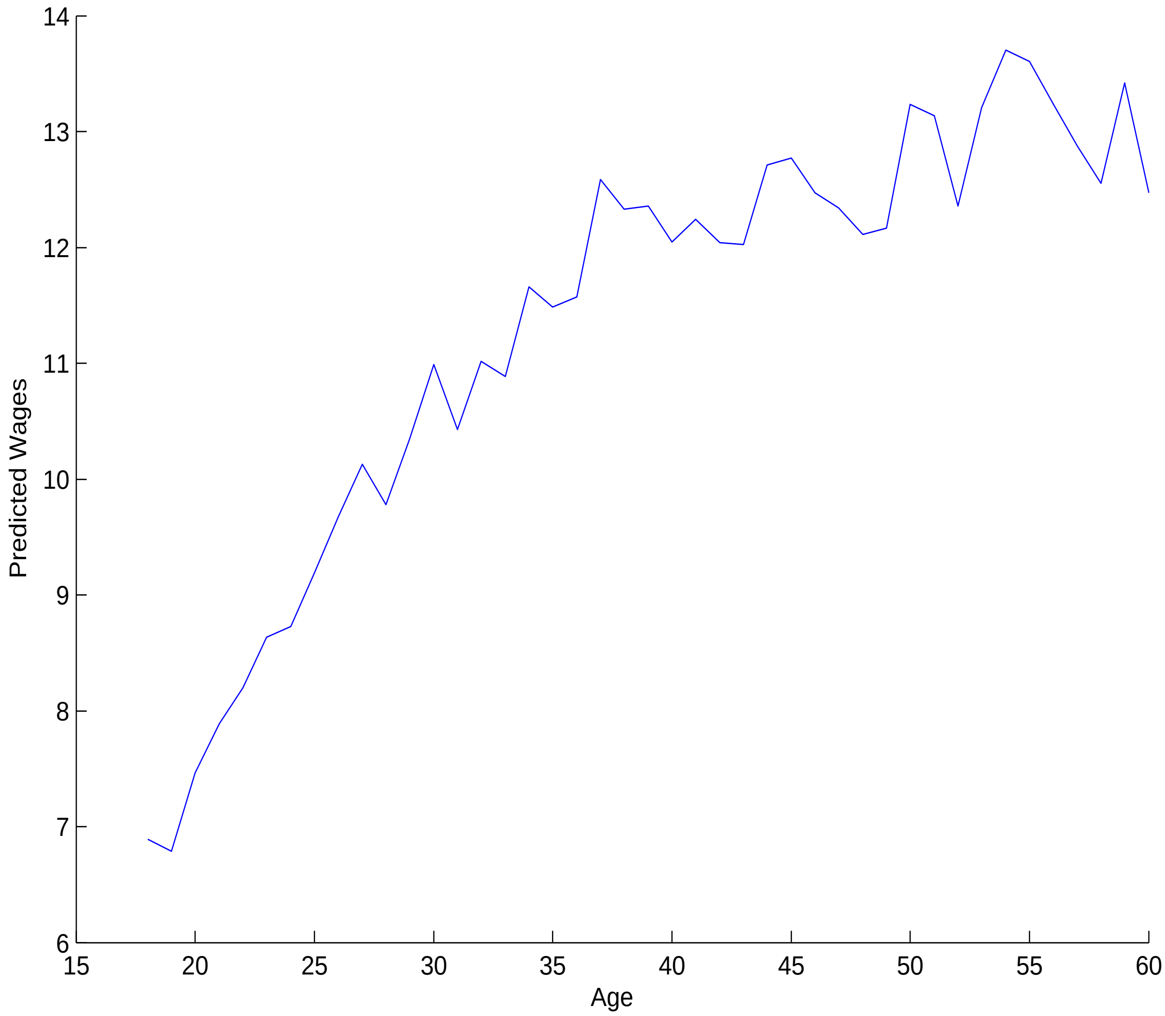
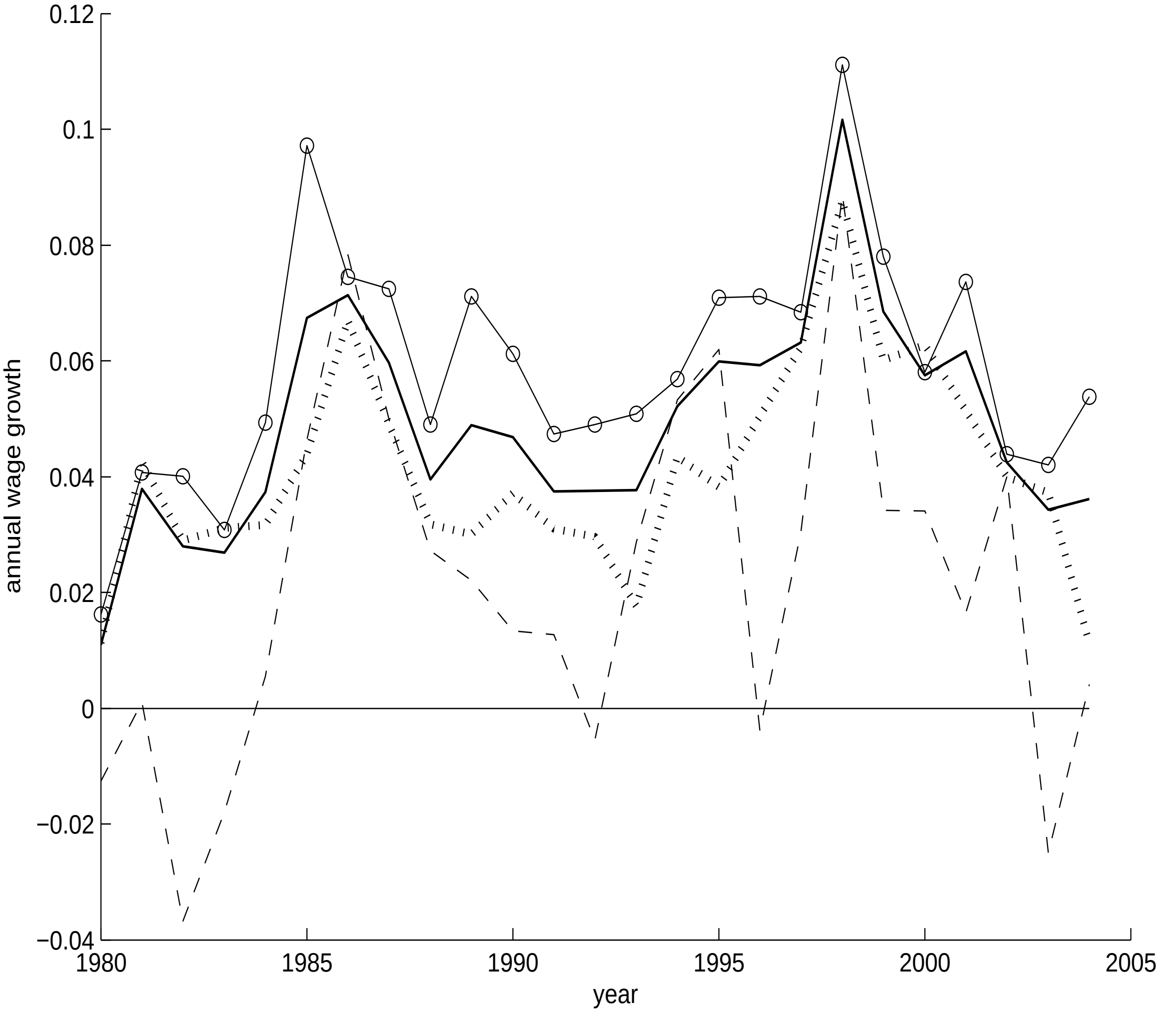


Figure 1: Log Wage Profile, Male, No College



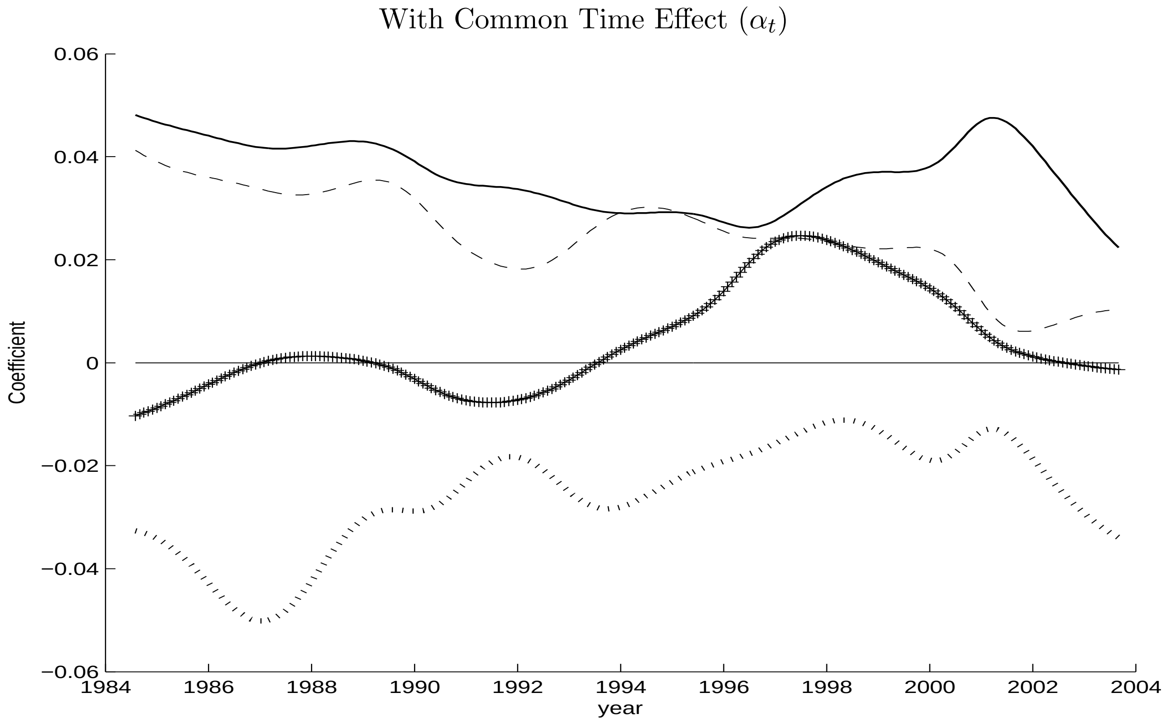
Solid Line All Workers

Dashed Line High School Dropouts

Vertical Line High School Graduates

Solid Line with O Beyond High School

Figure 2: Wage Growth 1980-2004, CPS by Education Group



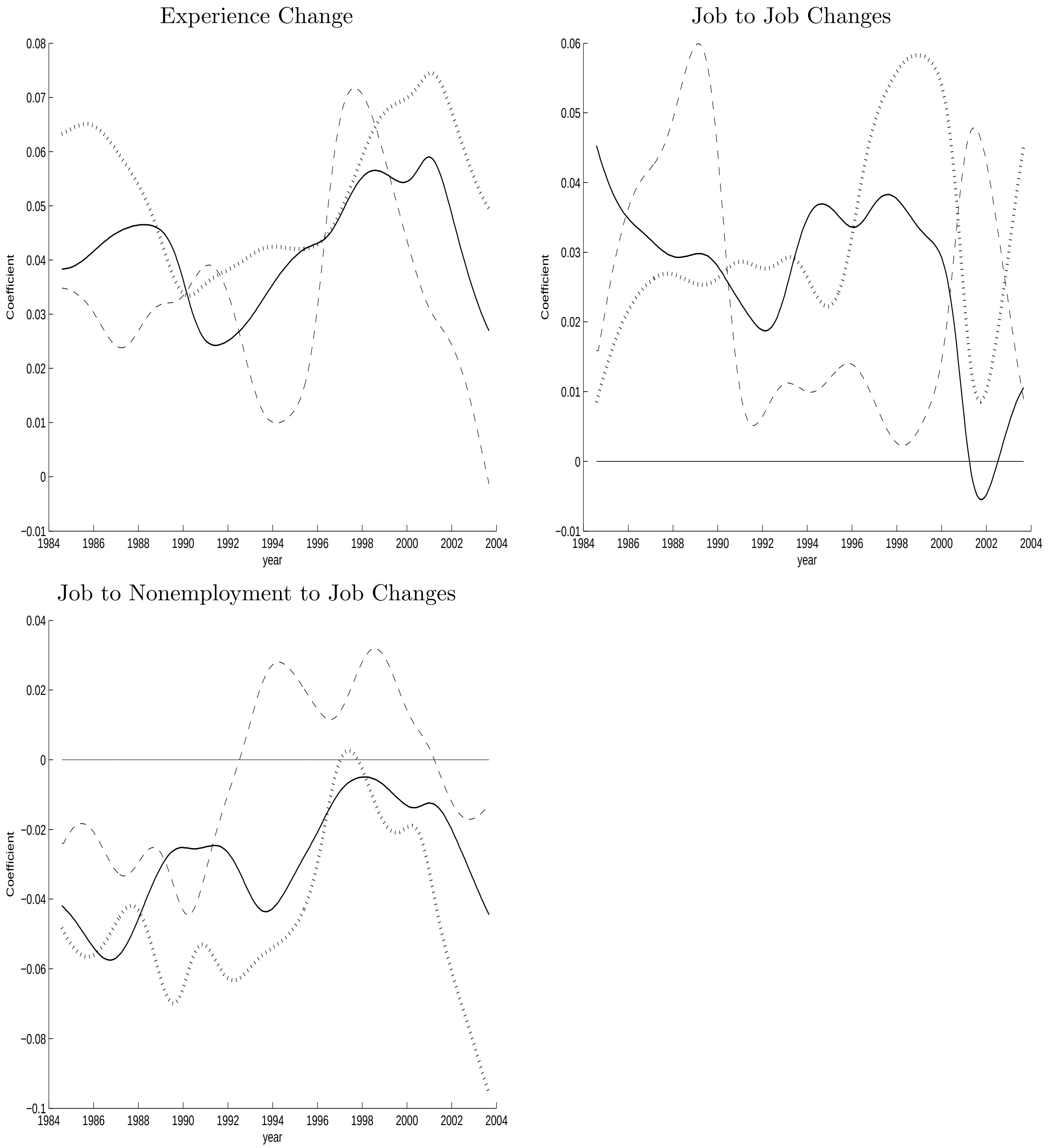
Solid Line Experience Change

Dashed Line Job to Job Transitions

Vertical Line Job to Nonemployment to Job Transitions

Solid Line with + Intercept change

Figure 3a: Coefficients Over Time (G_t), ages 18-28, no college

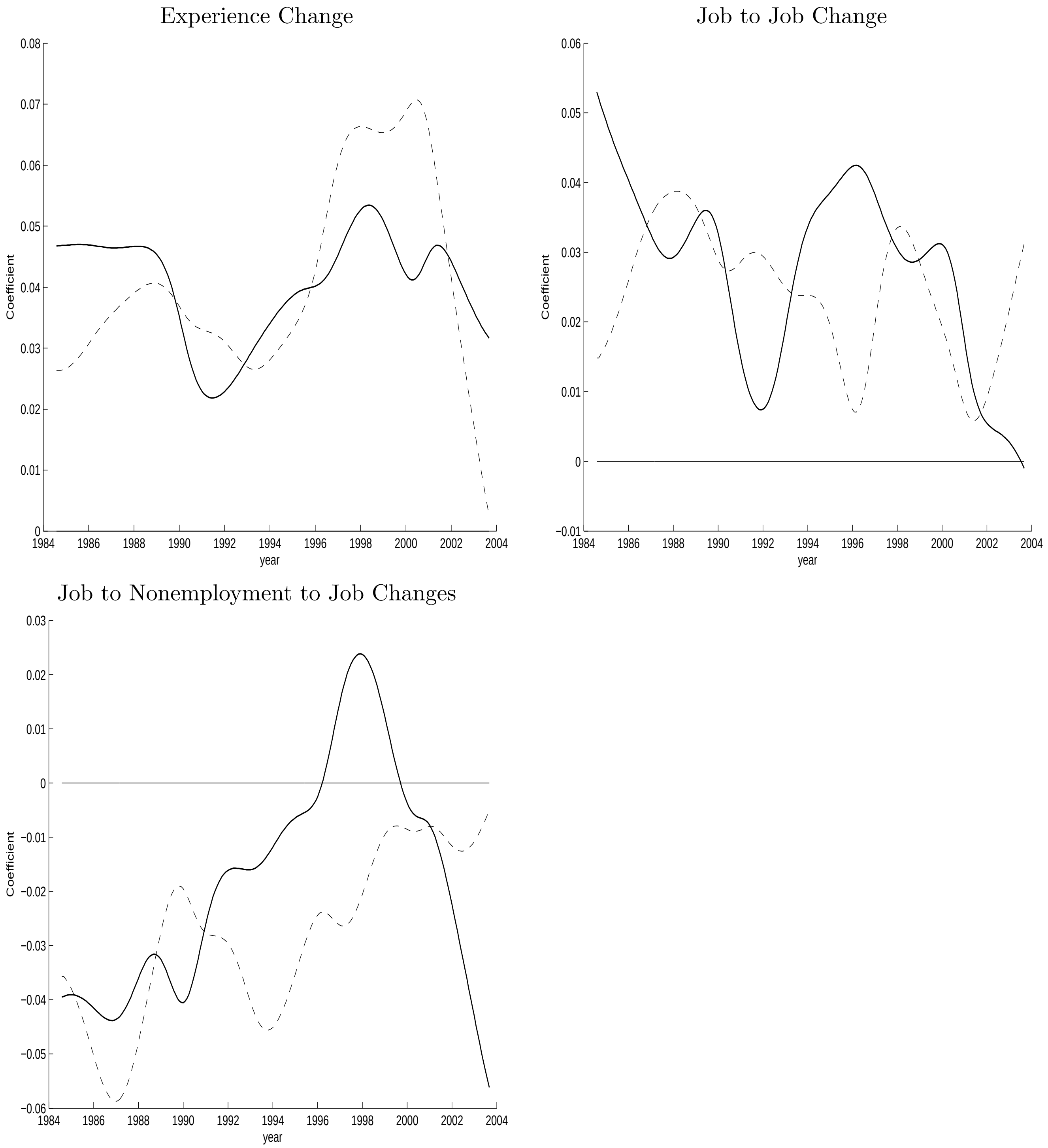


Dashed Line High School Drop Outs

Solid Line High School Graduates

Vertical Line College Attenders

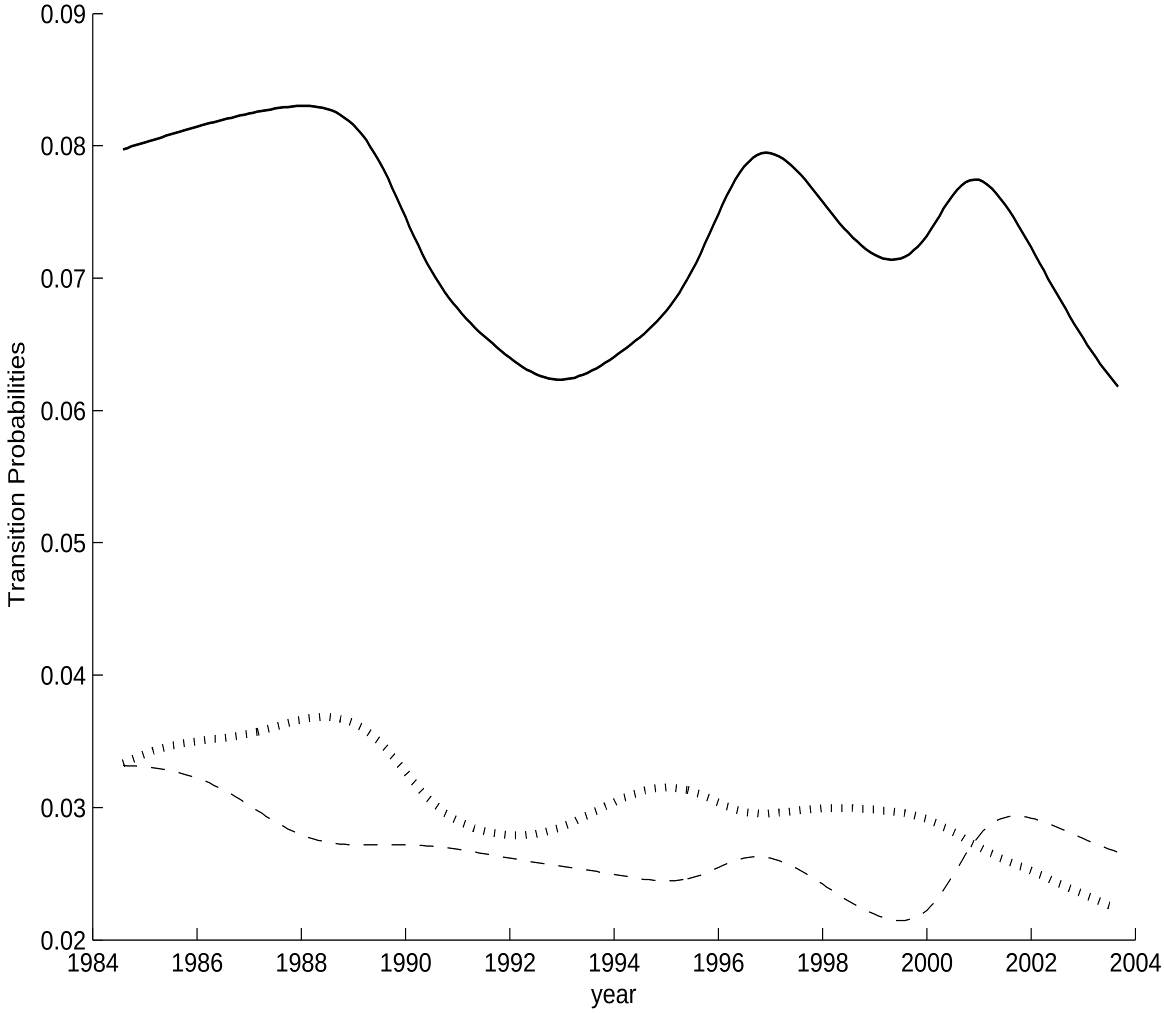
Figure 3b: Coefficients Over Time (G_t), by Education Group



Solid Line Men

Dashed Line Women

Figure 3c: Coefficients Over Time (G_t), by Sex

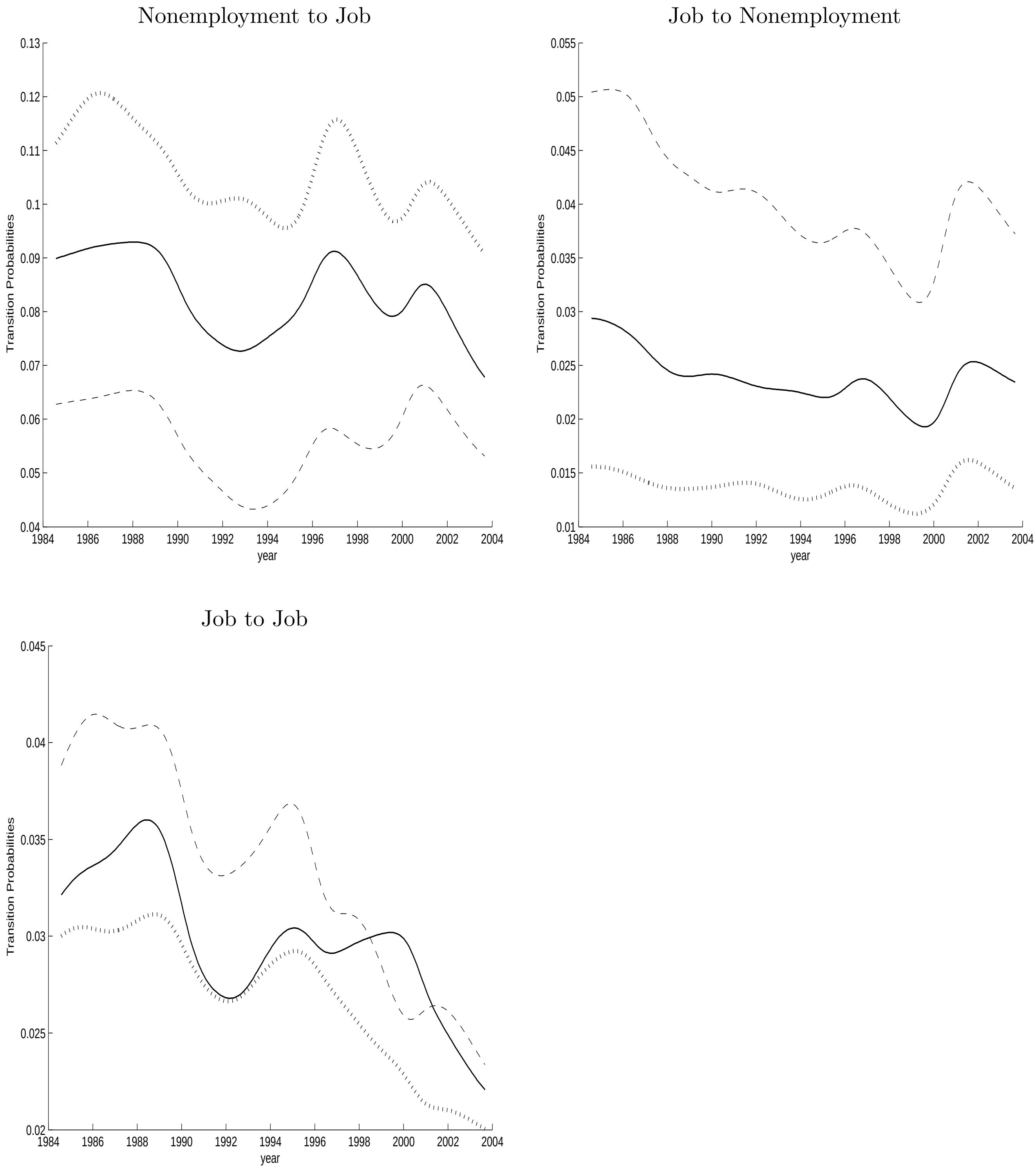


Solid Line Nonemployment to Employment Transition

Dashed Line Job to Nonemployment Transition

Vertical Line Job to Job Transitions

Figure 4a: TRANSITION PROBABILITIES, 18-28 YEAR OLDS, NO COLLEGE

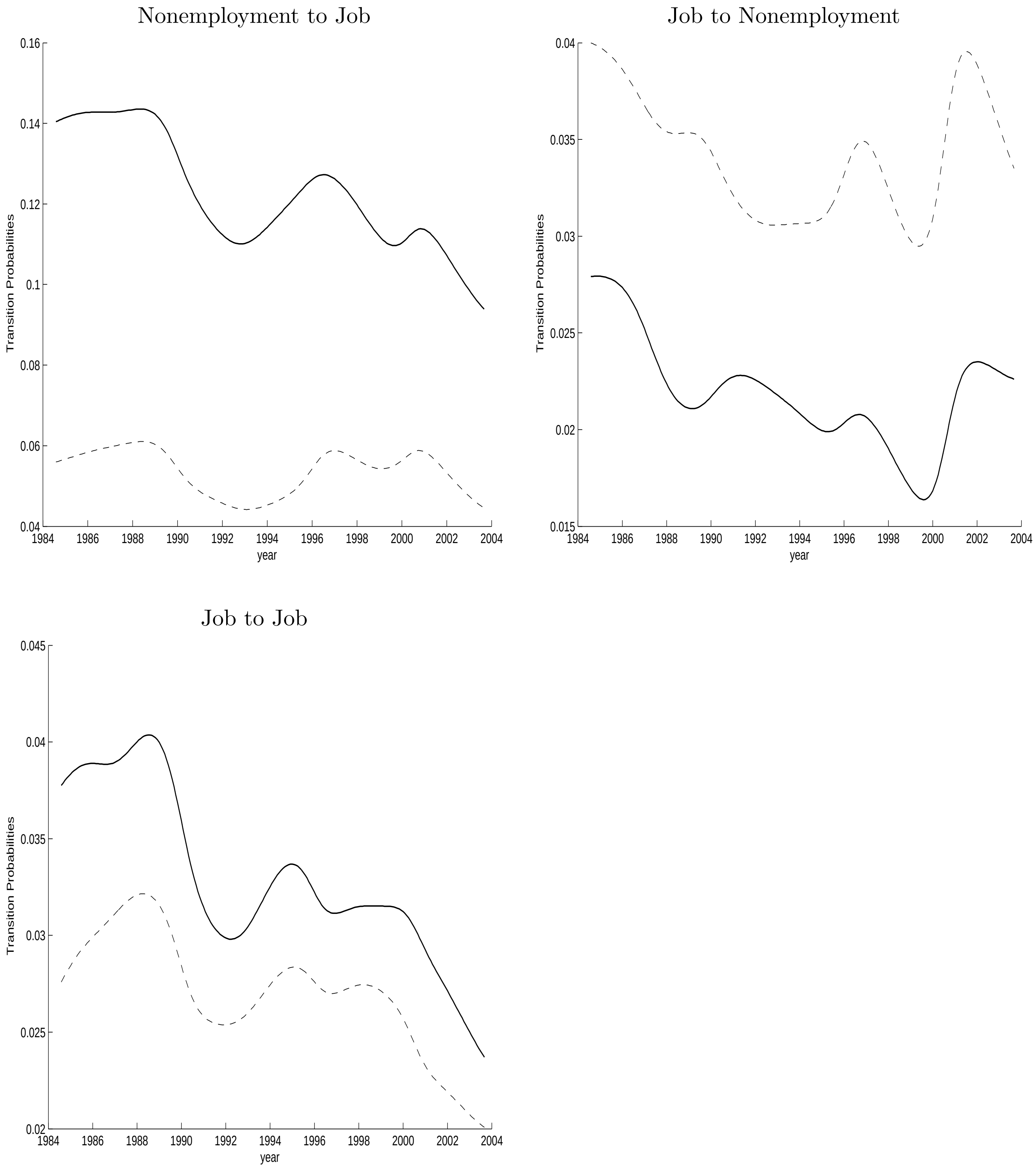


Solid Line High School Graduates

Dashed Line High School Drop Outs

Vertical Line College Attenders

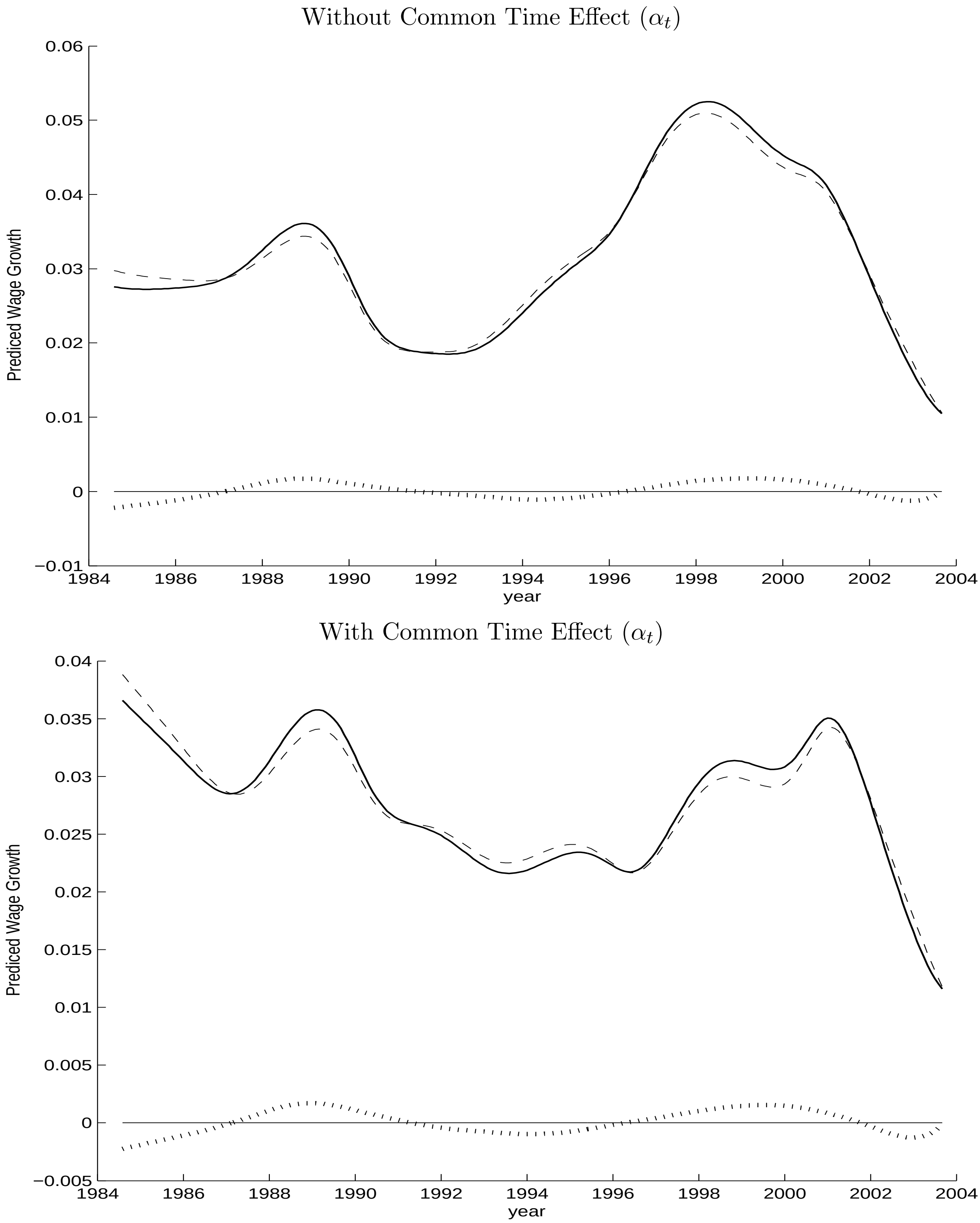
Figure 4b: TRANSITION PROBABILITIES, BY EDUCATION GROUP



Solid Line Men

Dashed Line Women

Figure 4c: Transition Probabilities, by Sex

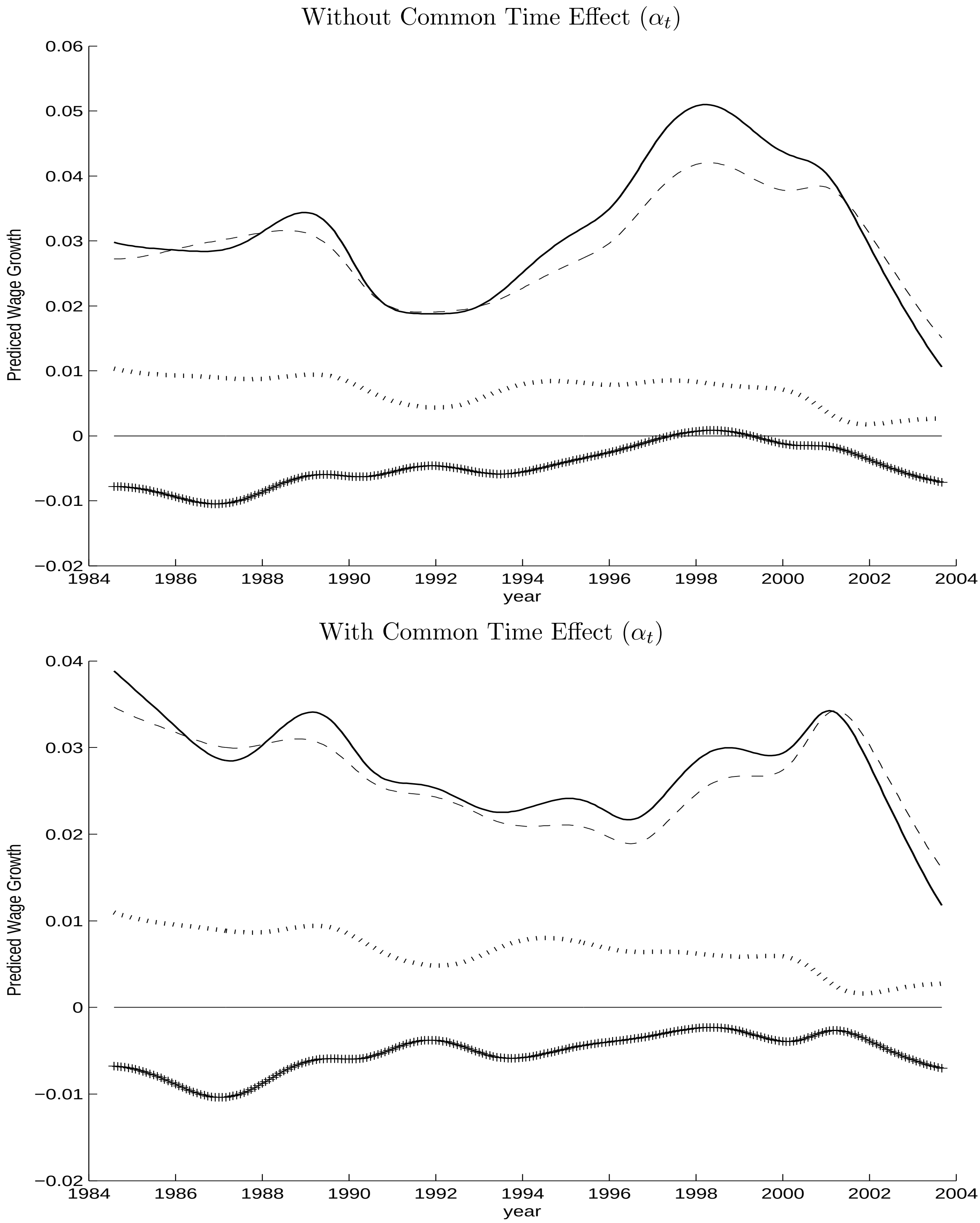


Solid Line Overall Predicted Wage Growth

Dashed Line Allowing Only Slope Coefficients (G_t) to Change

Vertical Line Residual Due to Factor (X_t) Changes

Figure 5: Predicted Wage, Decomposed into Subcomponents



Solid Line Overall Growth Due to Coefficients

Dashed Line Wage Growth on Job

Vertical Line Job to Job Transitions

Solid Line with + Job to Nonemployment to Job Transitions

Figure 6: Decomposition of Wage Growth: Coefficients