Estimating the Relationship between Employer-Provided Health Insurance, Worker Mobility, and Wages*

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Abstract

Two separate literatures have sought to quantify the relationship between wages and job tenure and quit decisions and employer-provided health insurance. The fundamental difficulty in both cases is the presence of unobservable person and job characteristics that are correlated with both compensation outcomes and personal mobility. This paper seeks to bring these two strands of research together by estimating a joint model of wages, hazard of a job ending, and probability of holding employer-provided health insurance and allowing for correlated person and job heterogeneity across the three equations. Using data from the 1990 and 1996 Survey of Income and Program Participation (SIPP) Panels linked to SSA administrative job histories, the model is estimable due to the presence of monthly wage, job tenure, and health insurance observations for a relatively large, nationally representative sample of people over the course of $2\frac{1}{2}$ and 4 years respectively. Multiple jobs per person and multiple observations per job allow the identification of the part of the variation in wages, tenure, and health insurance status due to unobservable person and job characteristics and the correlation between individual and job propensities for high wages, low mobility, and high probability of benefits. The explicit modeling of this correlation not only produces unbiased estimates of the tenure and health insurance effects, but also allows the comparison of hazard rates for high-wage jobs versus jobs with a high probability of providing health insurance. I find substantial levels of job-lock of 30%-60% and annual returns to seniority of 1.5%-2% after the first four years of a job. In addition, I find that increasing the job-specific probability of obtaining employer-provided health insurance from 60% to 73%, or increasing the job-specific hourly wage rate by $.80, are both associated with an equivalent 6% decrease in the hazard of the employer-worker match ending, although, on average, the dollar value of the wage benefit is higher.

1 Introduction

The relationship between compensation and length of time on the job has been modeled theoretically and tested empirically many times. Economists have recognized that firms may design compensation packages with the explicit intention of influencing decisions by workers concerning job duration and have sought to quantify the effects of particular types of compensation. Both theoretically and empirically, researchers have acknowledged the necessity of distinguishing between types of people and types of jobs that appear observationally equivalent but in fact have unobservable characteristics which influence both compensation and job duration.

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One of the most long running debates in this field has centered on the relationship between tenure and wages. Wages are observed to rise with job tenure above and beyond what can be attributed to accumulation of general labor market experience and quit probabilities are observed to decline with job tenure. Explanations for these empirical observations have included the development of firm-specific human capital, learning about job match quality, search, and individual heterogeneity. In evaluating these theories and determining whether tenure has a "true" effect on wages, controlling for individual and job quit propensities becomes essential.

A more recent debate has focused on the relationship between employer-provided health insurance and job duration. Health insurance has been termed "non-portable" because it is a job-specific benefit which is lost when a job is ended. This non-portability feature, along with the high incidence of people in the United States who sole source of health insurance is their employer, has led to a debate over "job-lock." This is the possibility that workers remain in job matches which would otherwise be dissolved due to the possibility that health insurance may not be available at a new job. Workers with pre-existing conditions or families with large medical expenses have been thought to be the most vulnerable to job-lock. However estimating a job-lock effect is complicated by the same person and job heterogeneity which influences wages. An observed decrease in mobility rates for people at jobs with health insurance may be due to the lack of portability of their health insurance, the high quality of their jobs, or their personal preferences for mobility.

This paper seeks to combine aspects of both these literatures by treating wages, job tenure, and employer-provided health insurance as three outcomes which result from the interaction of worker and firm choices. Using a statistical model proposed by Lillard (1999), this paper will estimate the relationship between these three variables in a way which treats each of them as endogenous and determined by both observable and unobservable person and job characteristics. Unobservable characteristics will be modeled using person and job random effects that will be correlated across equations, the feature of the model which prevents bias. The results from this statistical model will answer important questions about the relationship of various components of the compensation package to job tenure. Does holding a health insurance policy from an employer make an employee less likely to quit, even after controlling for person and job type and the fact that health insurance represents higher compensation? Are career high-wage individuals at high-wage jobs more or less mobile than career low-wage workers at low-wage jobs? Does longer job tenure increase wages in a causal way or is the correlation between tenure and wages the result of sorting heterogeneous workers into heterogeneous jobs? Finally, how do wages and health insurance compare in their effects on mobility?

Using the 1990 and 1996 Survey of Income and Program Participation (SIPP) Panels linked to administrative job earnings and job histories data from the Social Security Administration, I am able to construct detailed monthly information about my three outcome variables of interest: wages, employer-provided health insurance, and job tenure. My results show substantial levels of job-lock and returns to tenure of 1.5%-2% per year after the first four years of a job. High-wage workers are observed to be more mobile than low-wage workers while high-wage jobs are observed to last longer than low-wage jobs. A 5% log wage premium at a job reduces the hazard of the job ending by 6%. A rise in the probability of obtaining health insurance at a job from 60% to 73% reduces the hazard of that job ending by an equivalent amount even though this benefit costs the employer on average only 64% as much as the wage increase. These results point to the importance of the role of benefits as part of the compensation package and highlight the need for studies on the firm side to understand how profit-maximizing firms make choices about turnover and compensation.

2 Literature Review

2.1 Wages and Tenure

The literature on wage determination offers many theories for how tenure and wages may be related. One class of theories predicts tenure should have no effect after controlling for individual and match heterogeneity. If the work force is composed of "movers" and "stayers," mobility may decline with tenure because of a selection effect. Wages may rise faster for "stayers" because they are more likely to receive training by the firm. Search theory suggests that workers look for jobs which are good matches, where good matches are defined as high productivity pairings of workers and firms. These good matches pay more and hence raise the opportunity cost of leaving the job.

The mobility of these workers is reduced because of the decreasing probability of receiving a better offer (Jovanovic (1979), Burdett (1978)). Workers in bad matches with low earnings switch jobs in order to find better jobs and raise earnings. Hence the observation of a positive correlation between wages and tenure is simply a manifestation of match heterogeneity. On the other hand, human capital models predict that tenure affects wages because firm-specific human capital is accumulated and rewarded (Mincer (1974)). Search models also predict an effect of tenure if it takes time to determine the quality of the match (Jovanovic, (1979)).

Traditionally the relationship between wages and tenure has been estimated by including tenure as an explanatory variable in a wage equation. However as researchers moved towards viewing tenure as endogenous, methods to take this into account have developed. Abraham and Farber (1987) use expected completed job duration to instrument for seniority and find a return of .25%-.5% per year. Altonji and Shakotko (1987) also propose an instrumental variables approach, using deviations of the tenure variables around their means for a given job match as the instrument for tenure. They find a similarly small return to tenure of .6% per year. All these authors compare their results to a traditional return to seniority of 1% per year and conclude that person and job heterogeneity plays a role in the wage determination process. Topel (1991) also employs techniques to account for person and job match heterogeneity but finds a return of 3% per year to seniority and concludes that job-specific human capital is an important component of wages. Abowd et. al (1999) argue that person and firm heterogeneity should be directly modeled in the wage equation and that seniority should be treated as a firm-specific time-varying effect. They estimate a 1% return to a year of seniority. There is also evidence of effects in the opposite direction, of wages on tenure. For example, Topel and Ward (1992) estimate that a 10% increase in wages reduces the probability of changing jobs by 20%, while at the same time, job changes account for one third of total wage growth for male workers during the first ten years in the labor market. Results of this type lead to the consideration of another approach to solving the problem of estimating an accurate relationship between tenure and wages as proposed by Lillard (1999). He estimates a joint model of wages and tenure which deals with the issue of endogeneity by directly estimating tenure and allowing correlated person and job heterogeneity in both equations. He reports a return to job tenure of 5% for the first year, .6% for the second year, and .36% each year thereafter. Dostie (2001) estimates a similar model using French linked employer-employee data and finds no return to seniority.

2.2 Employer-Provided Health Insurance and Quit Decisions

A parallel literature has investigated the relationship between employer-provided health insurance and quit decisions. Until the mid-1980s, health insurance was a completely non-portable job benefit. COBRA legislation in 1985 made it possible to retain the old insurance for up to eighteen months if the worker paid 102% of the average cost to the old employer of continuing to provide the insurance (Madrian (1994)). However, for workers who faced pre-existing conditions clauses at new jobs that made them or their family members ineligible for new insurance, COBRA was only a temporary and expensive solution to the portability problem. In 1996, Congress passed HIPPAA, a new law that, among other reforms, limited the amount of time workers could be denied coverage for pre-existing conditions. These limits were based on how long the worker had previously held health insurance.

The literature on job-lock has attempted to measure the loss in mobility directly resulting from prohibitively high costs of losing employer-provided health insurance. This decrease in mobility can be viewed as a market failure which is efficiency decreasing. Due to the failure of the insurance market to provide health insurance policies for some types of people, unsuccessful job matches, the dissolution of which would have benefited the worker and the firm, are perpetuated. In measuring job-lock, the thought experiment one would wish to conduct is, "How much would the probability of leaving a job decline, holding all job and worker characteristics constant, if the compensation package changed from not providing health insurance to providing health insurance." This total change in the quit probability would be due to a compensation component and a job-lock component. The difficulty in actually performing this thought experiment is three-fold: holding the type of person constant, holding the type of job constant, and differentiating the compensation effect from the job-lock effect. Problems arise in such models because jobs that offer health insurance are likely to be "good" jobs and to employ "good" workers. Unobserved job and worker heterogeneity with regard to quit rates is correlated with the presence of employer-provided health insurance and unless one controls for this heterogeneity, the coefficient on the health insurance indicator will be biased. Insured workers will quit less often because of the quality of their jobs, their personal preferences for mobility, their relatively higher compensation in the form of insurance benefits, and the non-portability of their health insurance. Thus the goal of the literature has been to find a method for dealing with the endogeneity of the health insurance variable and to separately identify the effect of health insurance from the effect of the type of job, type of person, and compensation levels.

The most popular approach comes from Madrian (1994) and involves a difference-in-difference estimator. Using a probit model and data from the 1987 National Medical Expenditure Survey (NMES), Madrian estimates the probability that a worker who is employed at the beginning of the survey will end the job by the date of the second interview one year later. She includes indicator variables for holding employer-provided health insurance, and other, non-employer provided health insurance, as well as an interaction term between these two types of health insurance. She then calculates the probability of quitting a job for workers in four different groups: M_{11},those with both other and employer-provided insurance, M_{01}, those with only employer-provided insurance, M_{10}, those with only other insurance, and M_{00}, those with no insurance. Her difference-in-difference estimator is calculated as

$$(M_{11} - M_{01}) - (M_{10} - M_{00}).$$

Thus workers with employer-provided health insurance and presumably similar higher levels of compensation are compared to each other across a dimension thought to reduce job lock while controlling for the independent effect of this treatment effect. If job-lock exists then the difference-in-difference should be positive. Having other insurance should cause a greater change in mobility for those with employer-provided insurance than those with no insurance. She estimates that job lock reduces mobility by 31%. Others have obtained different estimates of job-lock using similar methods to Madrian but different data. For instance, Holtz-Eakin (1994) finds insignificant amounts of job-lock when he estimates a difference-in-difference model for married men with and without spousal insurance using the 1984 wave of the Panel Study of Income Dynamics (PSID).

The common critique of this approach is to suggest that unobservables about jobs and people are not differenced away and hence additional variables should be included in the probability model. For instance, Buchmueller and Valletta (1996) argue that workers with insurance through their spouses may have been offered insurance through their own employers and turned it down. These workers may thus have better jobs than those with no insurance and hence have lower mobility. This would lower the difference $(M_{10} - M_{00})$ in a way unrelated to the effect of insurance from another source. They propose additionally including pension coverage and tenure in the probit model to capture some of the firm and person unobserved heterogeneity. Using the 1984 Survey of Income and Program Participation (SIPP), they estimate that employer-provided insurance reduces turnover by 35-40% for women, but find insignificant effects for men.

Kapur (1998) offers further refinement of the difference-in-difference estimate using the 1987 NMES. In order to insure the comparability of the control and treatment groups, she uses only married men with employer-provided health insurance in her estimation. Those men without spousal health insurance form the experimental group and those with this additional form of health insurance are the control group. She then estimates a difference-in-difference model with the treatment variable being family sickness. Using this method, she finds no evidence of significant levels of job-lock.

Two papers offer estimation strategies other than the difference-in-difference model. Monheit and Cooper (1994) use the 1987 NMES to estimate reduced form wage and health insurance equations in order to predict compensation at a new job using data from voluntary job changers. Using the predicted likelihood of obtaining health insurance coverage at a new job, workers were classified into one of three categories: gaining insurance, losing insurance, or no change in insurance status. The predicted changes in wages and health insurance status were then included as explanatory variables in the probit quit model, along with indicator variables for other job benefits such as paid sick leave, percentage in the worker's industry covered by pension plans, and union membership, and indicators for other insurance coverage, spousal employment status, family size, and worker and dependent health problems. Since the health insurance change variable was estimated from individual and labor market characteristics, the authors maintain that it is not contaminated by unobservable job attributes. They find that those expected to lose coverage by changing jobs were between 3%-6% less likely to switch.

In the second paper, Gilleskie and Lutz (1999) propose testing for job-lock by including both offer and acceptance health insurance indicators in a job transition model. They offer two interpretations for the offered insurance variable. First, it could serve as a proxy for "good" jobs and measure the impact of job heterogeneity on the mobility decision separately from the impact of actually holding the non-portable health insurance benefit. Alternatively, it could represent what the authors term an "option-value," meaning that the offer holds value to the individual because of the potential to hold health insurance in the future, regardless of current take-up choices. Thus even an offer has the potential to cause job-lock. Using the NLSY from 1989-1993, the authors estimate a dynamic multinomial logit function which represents the likelihood of transitioning from the current job to each of the three possible future states. Without controlling for fringe benefits or health insurance offers, there is a 31% drop in job changes for married men when the individual has employer-provided insurance. The inclusion of an insurance offer variable reduces this to 12% and the additional inclusion of fringe benefit availability makes both the holds insurance and offered insurance variables insignificant. To test the robustness of their results, Gilleskie and Lutz estimate a joint probability model of initial tenure, employment status, marital status, the offer of employer provided health insurance, the holding of employer provided health insurance, the holding of health insurance from another source, and the employment transition decision and model unobserved individual heterogeneity as a person-specific random effect. This model again produces no evidence of job-lock for married men.

This literature on job-lock has arisen mainly in response to concerns about how to control for heterogeneity and how to account for the compensation effect of health insurance in lowering quit probabilities. Although many new types of controls have been used in the literature to solve these problems, some concerns still remain. The inclusion of tenure as an exogenous explanatory variable in order to control for person heterogeneity is problematic in that tenure is the result of a sequential set of quit decisions, each of which is correlated with the provision of health insurance by the employer. Fringe benefit variables such as pension coverage, included to control for job heterogeneity, may themselves be a source of job-lock and hence may control for more than just positive job characteristics. Since all data sets previously used have only one observation per job, distinguishing between job type and the particular effects of health insurance is difficult. Gilleskie and Lutz, for example, are only able to separately identify the health insurance equation separately from the job transition equation by using body mass index, number of jobs held (itself endogenous), and health limitations. Compensation effects are also possibly not well accounted for in the models previously discussed. The difference-in-difference model assumes that the compensation associated with employer-provided health insurance is constant across groups. However there is almost certainly a great deal of heterogeneity in the type and cost of offered insurance. Problems may arise when comparing employer-insured workers with and without health insurance through another person if the employer-provided policies are, on average, very different across the two groups. Those who chose to "double-insure" may have done so because their employer-provided policy had less generous benefits or more expensive premiums. Hence they are more mobile because they in essence receive less compensation. Another concern is that those with dual insurance sources may not tend to insure other family members as often as those with only employer-provided insurance. In addition to the direct effects of dependent family members on mobility, a family health insurance plan is worth substantially more than a single coverage plan and hence again represents higher compensation. These possible differences in compensation may artificially inflate the mobility of those with dual insurance relative to those with only employer-provided insurance. A final component of compensation which is also a concern is wages. Wages are universally included as exogenous variables in quit decision models although they are most likely jointly determined with tenure decisions.

3 Model

3.1 Estimating Health Insurance and Tenure Effects

My model will answer questions central to both the tenure and job-lock literatures and will contribute to each by including elements of the other. Following Lillard, I will view quit decisions, employer-provided health insurance, and wages as three outcomes of a joint process and hence treat each one as endogenous. Since the nature of my data will allow the estimation of a job duration model, I will use a hazard model formulation to estimate the probability of quitting conditional on the observed past job history. This essentially allows the estimation of a series of quit decisions over time. In estimating this system of equations, I will explicitly allow for both person and job heterogeneity by including individual and job random effects, with correlation between these random effects across equations. This correlation will account for the fact that workers with individual and job specific propensities for low turnover may have similar propensities for holding employer-provided health insurance and receiving high wages. Identifying job heterogeneity is made possible by the presence of multiple wage and health insurance outcomes for each job. This method will contribute to the job-lock literature by controlling for job heterogeneity in a new way, taking account of the effect of wages on job tenure in a way which does not assume that wages are exogenous, and modeling the actual tenure decision and not the probability of every individual quitting after the same arbitrary amount of time. The tenure literature will be advanced by the inclusion of other types of compensation in the tenure equation as well as the estimation of Lillard's model using another data source.

The effect of tenure on wages will be estimated using the coefficients on a tenure spline in the wage equation and the effect will be unbiased because of the heterogeneity controls. Evidence for the search or human capital theories of wage growth will come from the correlations of the person and job random effects across the tenure and wage equations. Testing for job-lock will not be quite as straight forward. I include an indicator variable for whether a person has employer-provided health insurance at a job in the hazard model for job duration and argue that the coefficient on this variable is unbiased because of the person and job random effects. However this coefficient will still contain the compensation effects of holding employer-provided health insurance. Thus to obtain an accurate measure of job-lock, I will use several methods of controlling for the monetary value of this benefit. First I will calculate a difference-in-difference model, following Madrian, where I compare those with and without health insurance through another person within the groups of workers with and without employer-provided health insurance. This will allow me to assess how my results compare to those of the literature and determine whether my controls for person and job heterogeneity reduce measured job-lock. Next to test the validity of the previously outlined concerns, I perform several specification checks where I control more specifically for what type of health insurance workers obtain from their employers, namely family coverage and how much of the cost of health insurance the employer pays.

In addition to these tests, I follow Gilleskie and Lutz and consider the effect of the inclusion of an "eligible but did not accept" health insurance indicator. Although my data on health insurance offers is not longitudinal, I use estimates of person heterogeneity from the main model to control for unobservable individual effects and allow the offer variable to proxy for job type. This model will provide a useful comparison to the model with job random effects.

The largest contribution of the full hazard-health insurance-wage model will be the estimation of the correlation between the job specific random effects from each of the equations. One can then compare the impact of above average wages at a job on the hazard of ending the job with the impact of an above average probability of having health insurance and assess the relative magnitudes of these two effects. This will allow an additional test of job lock. If health insurance is worth more to workers than an equivalent dollar amount of wages and we assume workers are being paid their marginal products, then this is evidence of rigidities in the labor market. Workers value their jobs more than the employer values their output and hence workers will be hesitant to leave for a more productive match if the compensation at the alternative job does not include the same mix of health insurance and wages.

3.2 Econometric Model

Following Lillard(1999), who estimated a joint model of wage and job duration, I propose the following three equation model:

$$\begin{aligned} HIEMP_{ijt} &= 0 \text{ if } HIEMP^* = \beta_{H1}X_i + \beta_{H2}X_{ij} + \beta_{H3}X_{ijt} + \gamma_i + \varepsilon_{ij} + \xi_{ijt} < 0 \\ &= 1 \text{ if } HIEMP^* = \beta_{H1}X_i + \beta_{H2}X_{ij} + \beta_{H3}X_{ijt} + \gamma_i + \varepsilon_{ij} + \xi_{ijt} > 0 \end{aligned} \tag{1}$$

$$h(t_{ij}) = e^{\gamma T(t_{ij}) + \alpha HIEMP_{ijt} + \beta_{HZ1}X_i + \beta_{HZ2}X_{ij} + \beta_{HZ3}X_{ijt} + \delta_i + \lambda_1\varepsilon_{ij} + \lambda_2\psi_{ij}} \tag{2}$$

$$S(t_{ij}) = \exp\{-\int_0^{t_{ij}} h(t_{ij})d\tau\}$$

$$f(t_{ij}) = h(t_{ij})S(t_{ij})$$

$$\ln(w_{ijt}) = \beta_{W1}X_i + \beta_{W2}X_{ij} + \beta_{W3}X_{ijt} + \theta_i + \psi_{ij} + \eta_{ijt} \tag{3}$$

where i is the person subscript, j is the job subscript, and t is the month subscript. The variables in the model are defined as follows:

$$
\begin{aligned}
t_{ij} &= \text{duration of job j for person i, time-varying across jobs} \\
HIEMP_{ijt} &= \text{employer provided health insurance, time-varying across and within jobs} \\
\ln(w_{ijt}) &= \text{natural log of hourly wage, time-varying across and within jobs} \\
(\delta_i, \gamma_i, \theta_i) &= \text{individual heterogeneity terms} \\
(\varepsilon_{ij}, \varphi_{ij}) &= \text{job heterogeneity terms} \\
X_i &= \text{person characteristics, time invariant across and within jobs -} \\
& \text{all equations - white, Hispanic, male, schooling} \\
& \text{health insurance equation - health condition} \\
X_{ij} &= \text{job characteristics - time-varying across jobs} \\
& \text{all equations - union status, industry, job type} \\
X_{ijt} &= \text{person and job characteristics, time-varying across and within jobs -} \\
& \text{all equations - marriage, number of kids} \\
& \text{job duration equation - any health insurance coverage, coverage from other person,} \\
& \text{interaction of coverage from other person and coverage from employer} \\
& \text{health insurance equation - hours worked per week, age begin job} \\
& \text{wage equation - general labor force experience, tenure, calendar time} \\
T(t_{ij}) &= \text{linear splines in age, job tenure, calendar time,} \\
& \text{general labor force experience which form baseline hazard} \\
\xi_{ijt} &= \text{time-varying component of probit error term, iid across months} \\
\eta_{ijt} &= \text{time-varying component of error term, iid across months}
\end{aligned}
$$

The problem in the estimation process occurs because the health insurance variable in the tenure equation (HIEMP in (2)) is endogenous and determined by person and job heterogeneity as shown in (1). If person heterogeneity in (2), δ_i, is correlated with person heterogeneity in (1), γ_i, then HIEMP is correlated with δ_i and α will be biased. Thus joint estimation of the three equations, allowing for cross-equation correlation of the heterogeneity terms, is necessary.

This system of equations is simultaneous in the heterogeneity parameters and is triangular in structure. HIEMP enters the job duration equation and tenure enters the wage equation. However wages are restricted to affecting tenure and health insurance through the correlation across the job and individual heterogeneity terms. Tenure affects health insurance in a similar way.

In controlling for worker and job heterogeneity, I will model the individual heterogeneity terms, δ_i, γ_i , and θ_i, as random effects that are jointly normally distributed with an unrestricted variance-covariance matrix.

$$
\begin{aligned}
(\delta_i, \gamma_i, \theta_i) &\sim N(0, \Sigma_{\delta\gamma\theta}) \\
\Sigma_{\delta\gamma\theta} &= \begin{bmatrix} \sigma_\delta^2 & \sigma_{\delta\gamma} & \sigma_{\delta\theta} \\ \sigma_{\gamma\delta} & \sigma_\gamma^2 & \sigma_{\gamma\theta} \\ \sigma_{\theta\delta} & \sigma_{\theta\gamma} & \sigma_\theta^2 \end{bmatrix}
\end{aligned}
$$

Likewise the job heterogeneity terms, $\varepsilon_{ij}$and ψ_{ij}, are distributed as

$$
\begin{aligned}
(\varepsilon_{ij}, \psi_{ij}) &\sim N(0, \Sigma_{\varepsilon\psi}) \\
\Sigma_{\varepsilon\psi} &= \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\psi} \\ \sigma_{\psi\varepsilon} & \sigma_\psi^2 \end{bmatrix}
\end{aligned}
$$

The time-varying health insurance and wage residuals, ξ_{ijt} and η_{ijt}, are normally distributed and are independent. The variance of ξ_{ijt} is not identified and so is normed to 1.

$$\begin{aligned} \eta_{ijt} &\sim N(0, \sigma_\eta^2) \\ \xi_{ijt} &\sim N(0, 1) \end{aligned}$$

Given these distributional assumptions, the variances and correlations of the random effects can be estimated. Identification of the variances of the person random effects, δ_i, γ_i, and θ_i, is possible due to the presence of multiple jobs per person. Likewise the identification of variances of the job random effects, ε_{ij} and ψ_{ij}, is possible due to multiple wage observations for a given job and the presence of people who switch health insurance status within a job. Since job duration is observed only once per job, it is not possible to estimate the variance of a job-specific random effect in the hazard equation. However the job random effects from the wage and health insurance equations can be included directly in the hazard model. Since the random effects have zero means, the coefficients on these effects, λ_1 and λ_2, will be estimates of the correlation between job specific hazard rates and propensities to have high wages and health insurance (Lillard (1999)). These estimated variances allow the calculation of realized random effects for individuals which represent individual propensities to end jobs, have health insurance, and have high wages. The estimated correlation coefficients allow the calculation of a conditional mean for one random effect given a certain draw for another random effect. For instance a negative correlation between δ_i and γ_i implies that a person with a higher than average propensity to have health insurance will have a lower than average propensity to have short jobs.

The model has a hierarchical structure with several levels of nested effects. The first level contains the probability of the observed job durations and employer-provided health insurance coverage, conditional on person and job heterogeneity. The next level models the probability distribution of the job effect and the third level models the probability distribution of the person effects. This nested structure has the result of estimating a different effect for the same job held by different workers. The parameters of the covariance-variance matrix, as well as the coefficients on the observable person and job characteristics for the hazard and health insurance equations, can be estimated by maximizing a likelihood function which combines the levels described above to represent the overall probability of observing each individual's job and employer-provided health insurance histories conditional on the job propensity to have health insurance and the person propensities to have health insurance and to have a job end. In general terms the likelihood can be written as

$$P(\text{Observed HIEMP and Job History conditional on person and job effects}) =$$

$$\int_\gamma \int_\delta \int_\varepsilon f(t_{ij} \mid \beta_{HZ}, \delta, \varepsilon) f(H_{ijt} \mid \beta_H, \gamma, \varepsilon) f(\varepsilon \mid \sigma_\varepsilon^2) f(\delta, \gamma \mid \Sigma_{\delta\gamma}) d\varepsilon d\delta d\gamma \tag{4}$$

The coefficients on the observable characteristics β_{HZ} and β_H, are assumed to have point-mass prior densities which is equivalent to leaving the distribution of these effects out of the hierarchy (Searle, Casella, McCulloch (1992)). Given the model outlined above, the likelihood function for individual i with $j = 1$ to J_i jobs, each lasting $t = 1$ to T_{ij} time periods is

$$L_i = \int\limits_{\gamma} \int\limits_{\delta} f\left(\gamma, \delta \mid \Sigma_{\gamma\delta}\right) \times \tag{5}$$

$$\int\limits_{\varepsilon_{iJ}} \left[\left\{ \prod_{t=1}^{T_{iJ}} [1-\Phi(\frac{\beta_H X + \varepsilon_{iJ} + \gamma_i}{\sigma_\xi})]^{1-d_{iJt}} [\Phi(\frac{\beta_H X + \varepsilon_{ij} + \gamma_i}{\sigma_\xi})]^{d_{iJt}} \right\} [h(t_{iJ})]^{D_{iJ}} S(t_{iJ}) \right] \phi(\varepsilon_{iJ})/\sigma_{\epsilon_{iJ}} d\varepsilon \times$$

$$\prod_{j=1}^{J_i-1} \int\limits_{\varepsilon_{ij}} \left[\left\{ \prod_{t=1}^{T_{ij}} [1-\Phi(\frac{\beta_H X + \varepsilon_{ij} + \gamma_i}{\sigma_\xi})]^{1-d_{ijt}} [\Phi(\frac{\beta_H X + \varepsilon_{ij} + \gamma_i}{\sigma_\xi})]^{d_{ijt}} \right\} h(t_{ij}) S(t_{ij}) \right] \phi(\varepsilon_{ij})/\sigma_{\epsilon_{ij}} d\varepsilon \times d\gamma d\delta$$

$$\begin{aligned}
d_{ijt} &= 1 \text{ if individual i has HIEMP at job j at time t} \\
&= 0 \text{ otherwise} \\
D_{iJ} &= 1 \text{ if last job ends} \\
&= 0 \text{ if last job is censored} \\
\beta_H X &= \beta_{H1} X_i + \beta_{H2} X_{ij} + \beta_{H3} X_{ijt}
\end{aligned}$$

The full estimation of equations (1), (2), and (3) adds the wage history to the likelihood. The probability of a worker's job and health insurance history is now made conditional on both the person and job random effects and the wage history. This conditional probability is then multiplied by the unconditional probability of observing the wage history. This can be written as

$$P(\text{Observed Wage, HIEMP and Job History conditional on person and job effects}) =$$

$$\int\limits_{\gamma} \int\limits_{\delta} \int\limits_{\varepsilon} f(t_{ij} \mid \beta_{HZ}, \delta, \varepsilon, W) f(H_{ijt} \mid \beta_H, \gamma, \varepsilon, W) f(\varepsilon \mid \sigma^2_{\varepsilon|W}, W) f(\delta, \gamma \mid \Sigma_{\delta\gamma|W}, W) f(W) d\varepsilon d\delta d\gamma$$

The full likelihood becomes

$$L_i = (2\pi)^{-T_i/2} \left|\Sigma_{\theta+\psi+\eta,\theta+\psi+\eta}\right|^{-1/2} \exp\left\{-1/2\left(W_i - \beta_w X\right) \Sigma^{-1}_{\theta+\psi+\eta,\theta+\psi+\eta} \left(\overline{W}_i - \beta_w \overline{X}\right)\right\} \times \tag{6}$$

$$\int\limits_{\delta} \int\limits_{\gamma} \phi(\gamma, \delta \mid \overline{W}_i) / \left[\Sigma_{\gamma\delta} \mid \overline{W}_i\right]^{-1} \times$$

$$\int\limits_{\varepsilon_{iJ}} \left[P(HIEMP_J) \left[h(t_{iJ})\right]^{D_{iJ}} S(t_{iJ})\right] \phi(\varepsilon_{iJ} \mid \overline{W}_i)/\sigma_{\epsilon_{iJ}|\overline{W}_i} d\varepsilon \times$$

$$\prod_{j=1}^{J_i-1} \int\limits_{\varepsilon_{iJ}} \left[P\left(HIEMP_j\right) h(t_{ij}) S(t_{ij})\right] \phi(\varepsilon_{ij} \mid \overline{W}_i)/\sigma_{\epsilon_{ij}|\overline{W}_i} d\varepsilon \times d\gamma d\delta$$

$$\begin{aligned}
\overline{W}_i &= \text{vector of wages over all months and jobs for person i} \\
\beta_w \overline{X} &= \beta_{W1} \overline{X}_i + \beta_{W2} \overline{X}_{ij} + \beta_{W3} \overline{X}_{ijt} \text{ vectors of X values} \\
P(HIEMP_j) &= \prod_{t=1}^{T_{ij}} [1-\Phi(\frac{\beta_H X H_{ijt} + \varepsilon_{ij} + \gamma_i}{\sigma_\xi})]^{1-d_{ijt}} [\Phi(\frac{\beta_H X H_{ijt} + \varepsilon_{ij} + \gamma_i}{\sigma_\xi})]^{d_{ijt}} \\
D_{iJ} &= 1 \text{ if last job ends} \\
&= 0 \text{ if last job is censored}
\end{aligned}$$

I will first estimate and report results for the hazard and health insurance pair of equations and then the hazard and wage pair. I will conclude with results from the full model.

4 Data Description

To estimate this model I will use the 1990 and 1996 panels of the Survey of Income and Program Participation (SIPP). The SIPP is a longitudinal data set which interviewed respondents between eight (1990 panel) and twelve (1996 panel) times and collected monthly data for the preceding four months. In the first interview (or wave) basic demographic information was collected as well as the date of labor force entry, years in the labor force, and start dates of on-going jobs. Then during each four-month reference period, information about the number of children, marital status, job status, wages, hours, job characteristics, and health insurance information was collected. This interview pattern produced monthly data for 32 and 48 months respectively, with the panels ending in mid-1992 and early 2000. The use of two SIPP panels will be advantageous for two reasons. First, all previous studies have been done using data from the late 1980s and early 1990s. Using the 1990 SIPP will allow for comparisons with these earlier studies. Second, given the amount of change in the health insurance market during the 1990s and the multiple changes in laws regarding the portability of health insurance, the 1996 SIPP panel will allow me to assess the importance of job-lock in the current labor market.

Each of my three outcome variables involves a time series of responses. The wage series for each job was constructed using self-reported hourly wage rates when the respondent reported being paid by the hour and monthly earnings divided by weeks worked and usual weekly hours when they reported being salaried. No imputed wage values were used. Jobs reported in the SIPP were given longitudinal ids with the intent that one be able to link jobs for a given respondent across waves and calculate job tenure. Start dates for jobs in progress at the beginning of the survey were also collected to enable duration to be calculated for these jobs. However in the 1990 SIPP panel there was substantial miscoding of job ids. Between 30-40% of the jobs were coded such that jobs either falsely link over time or erroneously fail to link. The later case affected approximately 10% of the jobs while the former affected 30% of the jobs. Thus the SIPP too often linked jobs which were in fact different, biasing job tenure upwards.

I attempted to solve this problem through a two step process. First, I used a statistical name matching software program to link the jobs reported in each interview by name of the employer, and then to create a set of unique job ids for each individual. Using these new job ids, I then compared job totals for individuals over the course of the SIPP to a secondary source of information. This information came from a confidential data set provided by the Social Security Administration to the Census Bureau for the purpose of improving Census core data products. This data set contained earnings histories broken out by employer for SIPP respondents over the time period 1978-2000. Using this data set I was able to count the number of jobs a person held during each of the years he or she was interviewed for the SIPP. I used this count to check the accuracy of the statistical name matches. Since the SIPP allowed reports on only 2 jobs and did not cover all months of the year in the first and last years of each panel, I expected the job count for a given individual to be higher in the SSA data than in the revised SIPP data. For respondents where this was not the case, I flagged the job histories as likely to contain too many jobs and did a second pass with the matching software. Problem cases left after this second pass were then hand-edited. The resulting total count of all jobs held by SIPP respondents was 24% higher than the original total count.

In 1996, the Census Bureau instituted Computer Assisted Personal Interviews (CAPI) for SIPP data collection and as a result the job data in this panel were much cleaner. There was essentially no false linking over waves and a much lower incidence of false non-linking. Using a similar procedure to 1990, I reduced the overall job count by approximately 4% by linking jobs with similar names. Many of these non-links resulted from people missing interviews, which caused difficulties in tracking jobs across breaks in survey responses.

Health insurance information collected in the SIPP included questions about whether a person is insured or not and if so, whether the source of that insurance is another family member, an employer, union, a previous employer, the military, or some other private source. Government health insurance programs such as Medicaid or Medicare were coded separately. Reports of employer-provided health insurance were not associated with reports about a particular employer, and hence it was necessary to assign this benefit to a particular job when there were multiple jobs. To do this I assumed that those holding multiple jobs were likely to have a full and a part time job and to obtain their health insurance from the "main" employer, defined by where they work the most hours or earn the most money. Thus, I selected on hours, followed by earnings if hours were equal. Care was taken in this process to prevent small fluctuations in hours from causing frequent changes in the health insurance source.

To make my sample representative and comparable to other research, I restricted myself to original sample members who held at least one job with non-zero earnings and who were not active duty members of the military. Jobs for these people were included when the job was begun at age 18 or older and ended or was censored by age 60; job duration was greater than one day; the employer was not a family business; an hourly wage of at least $.1 was reported at least once. Weighted summary statistics for the 1996 and 1990 Panels are presented in Tables 1a, 1b, 2a, and 2b respectively. My sample is fairly standard. SIPP respondents in the 1996 panel were 84% white, 49% male, and 62% were married in March 1996. On average, respondents held 1.98 jobs over the time period of the panel and 60% of people had employer-provided health insurance. Jobs lasted an average of four years, although the SIPP contains information about only 16 months of a job on average. This is due to the fact that many jobs were on-going when the SIPP began and many are missing wage information for several months during the panel due to non-response. The average job paid a real hourly wage (1999 dollars) of $15.01 in March 1996 and was held by a worker who worked 39 hours per week and who began the job at age 32 with 13 years of experience. The 1990 SIPP panel is quite similar to the 1996 panel with the only major differences being that 63% of people have employer provided health insurance, the average number of jobs held is 1.7, and the average hourly wage is $14.26.

Since variation in employer provided health insurance within job is an important component of my model, I investigated the causes of these types of changes in order to correct potentially false changes. Originally 17% of jobs contained at least one switch in employer provided health insurance status. These changes were compared to changes in other variables to determine whether the variation represented real coverage changes or survey response error. For instance, the SIPP allowed proxy respondents and hence in some waves a person responded for themselves while in other waves, a family member responded for them. In many instances where a health insurance switch took place, there was also a change in the person responding. In these cases, I recoded the health insurance variables to always contain the values reported in the waves without proxies.

Another difficulty occurred when the health insurance change took place in either the first or last three months of the job. While employers commonly impose a waiting period for insurance at the beginning of a job, this kind of a change is unlikely to be truly exogenous variation. The worker began the job with the expectation that he or she would quickly obtain insurance through the employer and perceived this to be part of the compensation. Including this kind of a change might bias the effect of health insurance on job duration because jobs which did not last longer than three months were less likely to have health insurance regardless of whether it would have been eventually offered. Likewise, the loss of health insurance in the last three months of a job was likely the result of the worker's decision to leave the job and hence either a preliminary switch to another kind of health insurance or a difficulty on the part of the SIPP in accurately coding the month of the health insurance change. Again, inclusion of this type of change would have biased the effect of health insurance. In this case it was the decision to quit which drove the health insurance change and not vice versa. As a result of these concerns, workers who gained health insurance from an employer during the first three months of a job or lost it during the last three months were coded as having employer-provided health insurance during the entire duration of the job. After recoding false health insurance changes, only 12.57% of jobs contain at least one switch in employer provided health insurance.

The major concern which remained was whether changes in health insurance status within jobs are exogenous. Since insurance changes are possibly correlated with "life events" such as marriage, divorce, addition of children to a family, or spousal employment changes, the hazard of quitting may be changed in a way unrelated to, but indistinguishable from, the direct effect of the health insurance change. Figures 1 and 2 investigate this problem by categorizing changes in employer-provided health insurance within jobs according to whether a worker gained or lost this insurance and concurrently, whether they gained or lost health insurance coverage of any other kind. As previously described for the 1996 panel and shown in Figure 1, workers changed the status of their employer-provided health insurance during 12.57% of jobs. These changes were almost equally divided between those who gained and lost employer-provided health insurance. Among employer-provided health insurance gainers, 36% previously had health insurance coverage through another person, 22% had a private policy in their own name, and 44% were not insured at all (these percentages sum to more than 100% because some people had two sources of insurance). Of those who had health insurance through another person, 70% kept this insurance after gaining coverage from their employers, while 30% dropped it. This is perhaps a surprising result and one of the major differences between panels. In 1990, of those who had been previously insured by another person, 79% dropped this insurance when they gained insurance from their employer(Figure 2). This result is consistent with the overall rise in dual coverage between 1990 (3.4%) and 1996 (5.1%).

The majority of those in the 1996 panel who lost health insurance through their employer, remained insured, either through another person (37%), through another type of policy in their own name (43%), or both (2% overlap). This again differs from 1990 where 32% of people gained private health insurance in their own name and thus larger numbers lost health insurance coverage completely. In 1996 of those who were prevented from becoming uninsured by having a policy through another person, 47% had held this coverage previous to losing health insurance from their employer. This compares to only 25% who previously held coverage through another person in 1990 (Figure 2).

Of the types of changes described above, those most likely to have been exogenous changes in health insurance are those who changed general insurance status (insured to uninsured or vice versa) and those who dropped or gained private policies in their own names. In each of these cases there do not appear to have been switches in spousal provision of health insurance, and hence these changes are more likely to have resulted from employer decisions regarding provision of health insurance benefits. It is possible that the worker changed his or her behavior in a way which changed his or her eligibility, by changing hours worked per week, for example. However for those who either became insured or dropped private coverage, only between 1% and 3% increased their hours by enough to move them from full-time to part-time. Those losing coverage completely or gaining private insurance decreased their hours by enough to move to part-time work between 4% and 6% of the time.

Changes in employer-provided health insurance within job which are also associated with changes in health insurance through another person are less likely to be exogenous. Workers who gain employer-provided health insurance and retain coverage through another person may have chosen to double insure, due to some change in family medical conditions, the addition of children, or simply a change from part to full-time status which caused the offer of health insurance at the job. However the changes that can be measured appear to be small. Only 1.25% gained children and 2% gained hours consistent with moving to full-time work. Those who gain employer-provided health insurance and give up coverage through another person are perhaps most likely to represent endogenous changes. These workers could have experienced divorce, spousal job loss, changes in the number of children in the family, or changes in hours worked. In fact 3.24% of these workers had spouses who ended jobs, 2.2% of them had a change in their number of children, .7% of them divorced or separated, and 3% of them gained hours consistent with moving to full-time status. All these changes together still affect less than 10% of the workers in this category.

Of those who lost employer-provided health insurance, between 4% and 6% lost hours consistent with moving from full to part-time work. Of those who switched from insuring themselves to having insurance through another person, 3% of these married, 9% had a spouse gain a job, and 1.6% gained a child in the family. Of those who were dual insurance holders and then dropped their own coverage, 1.4% gained a child in the family and 4% lost hours.

Taken together these changes provide some evidence that within job changes in employer-provided health insurance are not always correlated with "life-events" and so may be useful in identifying job heterogeneity. A worker who began a job without health insurance, possibly because it was only offered after an extensive waiting period, or because the worker had other insurance with which he or she was satisfied, or because the firm did not offer the benefit, and then after some time period switches to employer-provided health insurance, will have an underlying job-specific probability of having health insurance, identified by the months during the job with and without insurance. The inclusion of this job-specific health insurance probability in the hazard equation will account for correlation between the propensity for a given job to end and provide health insurance. The coefficient on the main health insurance indicator in the hazard model can then be interpreted as the change in the conditional probability of the job ending, holding all else constant, when the worker begins or ends employer-provided health insurance coverage.

5 Results

5.1 Results for Joint Health Insurance and Hazard Specifications

I begin by estimating equations 1 and 2 separately and then jointly. Table 3 provides results from the hazard model specifications. The hazard equation is estimated with piecewise linear splines in age, calendar time, labor force experience and job tenure as well as controls for union status, industry, job type and the demographic variables listed in the table. The baseline hazard is the probability of leaving a job conditional on the worker being non-white, female, single, age 32 years old, with no kids, no high school degree, 14 years of labor market experience, and job tenure of 0 months in March of 1996 at a non-union, private sector, wholesale trade job. The reported values for the health insurance and demographic variables are hazard ratios which are exponentiated hazard model coefficients. These ratios represent the probability of a worker with a given characteristic, X, leaving a job relative to the probability for an otherwise identical worker whose characteristics become the baseline and are summarized by βt. Thus these ratios can be thought of as

$$\frac{\exp\left(\beta t + \alpha X\right)}{\exp(\beta t)} = \frac{\exp(\alpha X)}{1}$$

Ratios less than one result when the characteristic, X, has a negative effect on the hazard of ending a job while ratios greater than one result when X has a positive effect.

The first three rows present hazard ratios for the health insurance coefficients of interest. The health insurance variables have been interacted with gender and marital status and therefore these hazard ratios are group-specific. The baseline person in this case is a married male with no health insurance. Column 1 presents results from estimating equation 2 alone with no random effects. Having health insurance from one's employer produces a hazard that is 34.7% that of the hazard for the baseline person, a 65.3% reduction. By comparison, having both employer-provided health insurance and insurance through another person gives a hazard that is only 48.4% of the baseline hazard, a 51.6% reduction. Thus the percentage increase in the hazard caused by moving from only employer-provided insurance to dual coverage is 28.9% [BOTH-HIEMPLOYER)/Both]. Those workers whose sole source of health insurance is another person are also less likely to end their jobs relative to an uninsured worker. The hazard ratio represents a 28% decrease from the baseline hazard. The percentage change in the hazard caused by the shift from non-insured to insured through another person is -39.1% [OTHER-1/OTHER]. The difference-in-difference effect reported in Table 3 is 68% [28.9%-(-39.1%)]. The effect takes account of the fact that alone, other insurance is associated with reduced mobility, and so the total effect of dual insurance both overcomes this negative effect and additionally further increases the hazard.

This difference-in-difference estimate is similar to methods used by Madrian and others in the literature but is not directly comparable because it represents a proportional shift in the hazard rate (i.e. a change in the conditional probability of ending the job at any point in time), instead of a change in the probability of leaving after a set amount of time. The large magnitude of this effect is a result of the large negative effect of insurance through another person on those for whom this is their sole source of insurance (HIOTHER). The literature also find a similar negative effect. The concern arises that having health insurance through another person, most commonly a spouse, signifies a certain type of person. These workers have better jobs and lower individual propensities to leave these jobs and so are not directly comparable to uninsured workers. Thus the -39.1% difference between the uninsured and those insured through other people is overstated because the comparison groups differ along dimensions other than the treatment effect.

Columns 2-4 take account of this critique by adding heterogeneity terms and treating the health insurance variable as endogenous. Column 2 shows results from the same specification as in Column 1 but with the addition of a person random effect in the hazard model. Column 3 presents estimates of equations 1 and 2 with person random effects correlated across equations and a job random effect included in equation 1. Column 4 lists results when the job random effect from equation 1 is included in equation 2. The joint estimation strategy and inclusion of random effects have the expected effect on the hazard ratio for employer-provided health insurance. The inclusion of heterogeneity but the failure to account for correlation between δ_i and HIEMP biases the hazard ratio even further downward in Column 2. When the joint health insurance, hazard model is estimated in Column 3, the hazard rises, a trend that continues in Column 4. This result lends support to the idea that taking account of individual and job propensities to have health insurance and be mobile reduces the direct effect of health insurance because downward bias is removed. The reported standard deviations and correlation coefficients provide direct evidence of the negative correlation between employer-provided health insurance and hazard rates. The correlation coefficient, ρ_{δ_γ}, is negative and significantly different from zero. This correlation is interpreted as predicting that workers with high individual propensities to have health insurance have low individual propensities to have jobs end. The coefficient from the hazard model on the health insurance job random effect, λ_1, is interpreted as the correlation between the job specific propensities for separation and holding health insurance. It is also negative although the correlation is not as strong as with the individual heterogeneity. Jobs which are more likely to provide health insurance have a lower hazard of ending.

In spite of the rise in the hazard ratio for employer provided health insurance, the difference-in-difference estimate remains fairly large and falls only very slightly in Columns 3 and 4. This is due to the fact that HIOTHER remains a significant negative predictor of mobility and the interaction term between HIOTHER and HIEMP remains fairly constant and positive. The inclusion of person and job heterogeneity does not change the effect of these variables and hence significant differences in hazard rates remain among those with only HIEMP and those with dual insurance coverage.

Table 3a presents hazard ratios for three other demographic groups: single men, married women, and single women. In all cases the hazard ratios follow the same pattern as for married men. The hazard for employer-provided health insurance rises in Columns 3 and 4 while the hazard ratio for health insurance through another person remains fairly constant. The hazard ratio for dual coverage moves in tandem with the ratio for HIEMP, indicating a positive and constant interaction term. The difference-in-difference effects remain positive. The level of these effects, however, differs substantially depending on the group. Single men see a much smaller rise in the hazard of a job ending due to the presence of a second source of coverage (16%). Married women have the largest levels of job lock. An additional source of health insurance increases their hazard by over 80%. Single women have lower levels than married workers but higher levels than single men.

Figure 3 shows relative hazard rates for four different groups of workers beginning jobs in March 1996 over the first 48 months of a job. The base person is a white, non-Hispanic, married man, age 32 years old with one child, a high school education and 14 years of labor force experience, beginning a non-union, private sector job in the wholesale trade industry. The hazard over time is generated using the tenure spline coefficients. The probability of quitting at time t conditional on the job having lasted until t-1 peaks at three months and then tapers off sharply until six months, when it levels out and decreases more gradually. The hazard for those workers who have employer-provided health insurance but are otherwise identical to the base person is substantially lower. The hazards for those with dual insurance and those with only insurance from another person lie in between the base and HIEMP workers. This figure gives a graphical presentation of the difference-in-difference result and shows the dramatic impact of health insurance benefits on the probability of a job ending.

Table 4 gives the results from the probit health insurance model which correspond to the results in Table 3. The outcome variable is a zero/one indicator for whether the worker had employer-provided health insurance in a given month. In column 1, no person or job heterogeneity is included. In Column 2, person and job heterogeneity are added and in Column 3, the probit is estimated jointly with the hazard equation and correlation across equations in the person heterogeneity is allowed. In Column 4, job heterogeneity is allowed to enter the hazard equation directly. The signs on the coefficients are fairly constant across specifications. More educated workers and those who work 20 hours or more per week are more likely to have health insurance, while workers with chronic but non-severe health conditions such as asthma, back pain, or diabetes are less likely. Women who are married and women who have children are less likely to have employer-provided health insurance. However the interaction terms are such that these negative effects are almost completely overridden for men. The first two rows of Table 4 presents standard deviations for the person and job random effects. These standard deviations are relative to the normed standard deviation of the time-varying iid residual. Their magnitudes imply that unobservable individual characteristics account for 18 times as much of the variation in health insurance status as the time-varying residual while unobservable job characteristics account for 7 times as much.

Table 5 presents results from the same specifications as in Table 3 but for the 1990 SIPP Panel. Due to the introduction of new portability laws in July 1997 (HIPPAA) which restricted employers' ability to deny coverage because of pre-existing conditions, one would expect job-lock to be substantially higher in 1990. In fact this is true only for single men and women. The difference-in-difference estimate of job-lock is 52% and 65% respectively, compared to 16.5% and 36% in 1996. For married men and women, the difference-in-difference estimate is very similar across panels, 61% and 86% in 1990 compared to 67% and 86% in 1996. While this model is not meant to be an explicit test of HIPPAA, it does provide some circumstantial evidence that the effect of the new law has either been somewhat limited or slow to have an impact on mobility.

The results from Tables 3 and 5 seem to point to significant interactions between family status, spousal employment status, and the effect of various types of health insurance. This is almost certainly the result of both the independent effects of spousal employment and health insurance holding and some heterogeneity in the types of employer-provided health insurance held by workers with and without alternate coverage sources. I consequently estimate three specification checks for whether the type of employer-provided insurance has an effect on the level of job-lock. In table 6 I divide workers with employer-provided health insurance into three categories: those who cover only themselves, those who cover one other family member, and those who cover multiple family members. Using this definition of health insurance benefits, those who cover only themselves experience a much larger increase in mobility when they have a second source of health insurance. The difference-in-difference estimate of job-lock is 62% for insure-self-only workers compared to only 34% for insure-multiple-family-members workers. However it is possible that this merely reflects the fact that workers with families are less mobile due to family reasons and hence having an optional source of health insurance does not increase the hazard by as much.

Table 7 investigates the issue of whether the amount of compensation associated with the health insurance benefit has any influence on the level of job lock. Here the results are quite striking. For those workers who pay none of the cost associated with their employer-provided health insurance, the addition of another source of coverage will increase mobility by 29%. For those who pay part of the cost of HIEMP, dual coverage increases their mobility (raises the hazard) by 41%. However for those who pay all of the costs, having additional coverage lowers the hazard relative to those who only have HIEMP. In this case, there would appear to be almost no compensation component of the health insurance effect and hence the hazard ratio for these workers can be interpreted as a measure of job-lock. As reported in columns 1 and 2, workers who pay all their premiums still experience a 20-36% reduction in mobility The difference between the hazard ratios of those workers who pay all and those who pay none of the health insurance costs represents the compensation component of the health insurance effect on mobility. In column 1 this difference is 29% which is about 45% of the total decrease in the hazard ratio when the worker has a paid-in-full health insurance benefit.

Finally in Table 8, I test the effect of the inclusion of an "offer health insurance" variable. Individuals who do not have health insurance from their employer during the fourth reference month of the fifth wave of the survey (July-October 1997 depending on the rotation group) are asked a set of questions in order to determine the reason for this lack of coverage. Using these responses it is possible to determine whether a worker was eligible for health insurance and turned the offer down or whether no offer was made. Unlike the more general monthly health insurance information, however, this information is specific to the job which was on-going during the fifth wave and is not longitudinal in nature. Hence this estimation differs slightly from that used in the previous tables. I estimate a hazard model using only jobs which cross the July-October 1997 time period jointly with the full hazard, health insurance specification and include the individual heterogeneity from the full model in the reduced-sample hazard equation. The hazard ratio for those who are eligible for HIEMP represents a 47.7% reduction in the hazard relative to someone without a health insurance offer. For those who are both eligible for and accept HIEMP, there is a further reduction in the hazard of the job ending. The difference between these two hazard ratios is 13.9%, implying that the acceptance of the health insurance offer reduces the hazard by an additional 36% relative to a non-take-up worker. Also of interest is the fact that the hazard ratio for those with health insurance through another person is no longer significantly different from one. Taking account of health insurance offers may reduce the importance of this variable because controlling for offers also proxies for job type. Although the magnitude of job-lock is smaller in this model, there is still a significant reduction in mobility due to employer-provided health insurance.

5.2 Results for Joint Wage and Hazard Specifications

Table 9 presents results from the joint estimation of the hazard and wage equations. Coefficients from the tenure and general labor market experience splines are reported, as well as the coefficients of basic demographic variables. In the first column, the coefficients are from a simple linear wage regression . In the second column, person and job random effects are added to the wage regression. In the third column, the wage and hazard models are jointly estimated and correlation across the equations in the person heterogeneity components is allowed. In the final column, wage job heterogeneity is included in the hazard equation and a correlation coefficient on this effect is estimated. Comparing the tenure coefficients across these four specifications shows the effects of controlling for heterogeneity and endogeneity bias. Adding heterogeneity substantially decreases the return to seniority during the first year of the job. In column 1, an additional month of tenure after three to six months on the job implies a .006% increase in log wages, an annual rate of 7%. The effect during the sixth to twelfth months is similar. However by adding heterogeneity terms, these effects fall significantly to an annual rate of approximately 3.5% over the course of the third to twelfth months. In column 1, returns after the first year are substantially lower and represent annual rates of return to seniority of 1%-2%. These rates are also more stable across specifications. Perhaps most surprising is that there are few differences in the tenure spline coefficients between columns 2, 3 and 4. Making tenure endogenous does not seem to have a significant impact on the tenure coefficients.

Hazard ratios from the job duration part of the joint estimation in columns 3 and 4 are not reported but are fairly similar to the results in columns 3 and 4 of Table 3. One of the most informative parts of this joint model is the relationship between the person and job random effects in each equation. The standard deviations of the random effects are reported in Table 9 as well as the person and job cross-equation correlation coefficients. These correlation coefficients, $\rho_{\delta\theta}$ and λ_2, have opposite signs in column 4. The positive correlation between the person effects in the wage and hazard models ($\rho_{\delta\theta} > 0$), implies that high-wage workers are also likely to be "movers" in that they have high individual propensities to have jobs end. On the other hand, the negative correlation between the job effects ($\lambda_2 < 0$), implies that jobs with high wages are also jobs which are less likely to end. These results are consistent with search models where there are returns to changing jobs because match quality rises and workers who are observed to engage in search benefit in the form of higher wages. However, once a worker has found a good match in the form of a well-paying job, he or she becomes less mobile.

5.3 Results for Joint Wage, Hazard, and Health Insurance model

Results for the full three equation model are reported in Table 10 for both the 1996 and 1990 SIPP Panels. Standard deviations of all the random effects are reported as well as correlation coefficients, health insurance hazard ratios from the tenure equation, and tenure coefficients from the wage model. This specification allows the random effects in all three equations to be correlated and provides measure of seniority and health insurance effects which take this correlation into account. The signs of the correlation coefficients are again instructive about the matching process and the estimated biases likely to arise if heterogeneity is not explicitly modeled. Job heterogeneity from both the wage and health insurance equations is associated with lower probabilities of a job ending ($\lambda_1, \lambda_2 < 0$). However the correlation is much higher for wages than for health insurance. This result implies that highly compensated worker-job matches are less likely to end, possibly either because the match is very productive for both sides or because the opportunity cost of leaving the job is high for the worker. On the person heterogeneity side, the correlations between wages and mobility and health insurance and mobility have opposite signs. Workers likely to have health insurance are also less likely to have jobs end ($\rho_{\delta\gamma} < 0$), while high wage workers tend to be more mobile ($\rho_{\delta\theta} < 0$ in 1996 panel although not in 1990). Individual and job propensities for high wages also tend to be associated with individual and job propensities for health insurance ($\rho_{\theta\gamma}, \rho_{\psi\varepsilon}$).

The results of controlling for these correlations are consistent with the hypothesis that heterogeneity biases seniority coefficients in wage models and health insurance coefficients in tenure models. Tenure effects average 4% during the first year and fall to approximately 2% after four years. These results are very similar to those shown in column 4 of Table 9, indicating that the inclusion of the health insurance equation did not substantially alter the results from the wage equation. On the other hand, the hazard ratio for employer-provided health insurance rises to approximately 60%, substantially higher than in Table 3. In this model, the magnitude of job lock can be estimated in two ways. First, one can use the standard difference-in-difference technique discussed previously and compare those with dual insurance coverage to those with health insurance coverage only from an employer and then subtract the independent effect of insurance coverage through another person. This difference-in-difference estimator (last row of Table 10) predicts a 56%-64% drop in the hazard of a job ending when the employee holds work-related health insurance. This effect remains large because other insurance continues to reduce mobility when it is the only type of insurance held but increase mobility when it is a second source of insurance. The difference-in-difference estimate is lower in 1996 than in 1990, but only by 8%.

Another alternative to using the difference-in-difference method is to consider the implications of the random effects. For example, consider a worker who earns \$16.50 per hour on average during the SIPP panel, a pay rate which is \$1.50 (.1 log wages) more per hour than the March 1996 sample average of \$15. For simplicity, assume the worker held only one job and was observationally equivalent to the "average" worker earning \$15 per hour. Using the variance estimates, σ_θ, σ_ψ, and σ_η, one can predict values for θ_i and ψ_{ij} which estimate how much of this "excess" wage is due to unobservable person and job characteristics[1]. In this example, θ_i = \$.684 (.0456 log wages) and ψ_{ij} = \$.807 (.0538 log wages). The remaining amount is due to random time variation. Given this realized value for ψ_{ij}, one can then predict a new conditional mean for the job-specific component of the hazard using the correlation coefficient λ_2 by calculating E(job effect in hazard model | ψ_{ij})[2]. This produces the result that a job-specific wage premium of .053 log wages reduces the mean of the job-specific effect in the hazard equation to -.064, which represents a hazard ratio of 94%, or a reduction of 8%.

A positive value of ε_{ij}, or an increase in the probability of having employer-provided health insurance due to unobservable job characteristics, similarly reduces the hazard of the job ending. This effect works in two ways. First an increase in ε_{ij} reduces E(job effect in hazard model | ε_{ij}) due to the negative sign on λ_1. For example, a predicted value of $\varepsilon_{ij} = .37$ would produce E(job effect in hazard model | ε_{ij}) = -.00689. Second, an increase in ε_{ij} increases the probability of having employer-provided health insurance which affects the hazard directly. For an individual with an initial probability of having employer-provided health insurance of 60%, ε_{ij} increases this probability to 73.4%, a change of 13.4%. Using the coefficient on HIEMPLOYER from Table 10, column 2 (ln(.64)), this rise in the probability of having health insurance reduces the hazard by -.06. Combining the two effects produces a total effect on the hazard of -.066, or a hazard ratio of 94%, a magnitude comparable to the effect of a 5% job specific log wage premium.

Although no information is available in the SIPP about the cost to employers of providing health insurance policies, national averages provide some insight into the monetary value of health insurance benefits. Branscome and Brown (2001), using data from the 1998 Medical Expenditure Panel Survey, report that the average health insurance premium for an employer-provided single person coverage policy is \$2,174, of which the employer pays on average 82.4% (\$1,791). Thus a job which predicts a 13.4% increase in the probability of having single person employer-provided health insurance coverage also predicts a \$283 gain in expected compensation. Family coverage costs an employer \$4,208 on average and a 13.4% rise in the probability of having family coverage represents a \$564 expected gain. By comparison, a worker with a 5% job log wage premium compared to the sample average wage of \$15, earns an additional \$1,604 per year. Assuming a 45% total tax rate, this is equivalent to \$882 in real increase for the worker. Thus reducing the hazard of a worker quitting by 6% by increasing the probability of providing that worker family health insurance benefits will cost a firm on average 64% of what it would cost to obtain the same reduction in mobility by increasing wages. This result is again consistent with the existence of job lock because the total compensation package if worth more to an employee than it costs the employer to provide it. Hence an alternate employer could not lure the employee to a new job by promising slightly higher compensation but all in the form of wages. Workers who have reason to believe they will be denied health insurance coverage at a new employer will not accept the offer even if the job pays higher wages.

6 Conclusions

My joint estimation of job duration, health insurance status, and wages explicitly takes into account many of the concerns arising in the estimation of the effect of employer-provided health insurance on the probability of a job ending and of the effect of tenure on wages. By controlling for person and job heterogeneity and allowing this heterogeneity to be correlated across equations, I am able to account for unobservable person and job characteristics which might otherwise bias the coefficients on tenure and health insurance. In spite of these controls, all of my specifications show some level of job lock (ranging from 30%-60%) using data from both the 1990 and 1996 SIPP panels. Controlling for person and job heterogeneity mitigates the direct negative impact of employer-provided health insurance but does not substantially change the effect of insurance from another source. Insurance through another person decreases mobility when it is held alone and increases mobility when it is an additional source. There

[1] Searle, Casella, and McCulloch (1992) derive a Best Linear Unbaised Predictor (BLUP) for a linear model with a normally distributed, mean zero random effect as $BLUP(u) = \frac{cov(u,y)}{var(y)}\left(y - \mu_y\right)$.

[2] $E(x \mid y) = \frac{cov(x,y)}{var(y)}(y - \mu_y)$ which for this model is

$E(\text{job specific hazard rate} | \ \psi) = \frac{\lambda_2}{\sigma_\psi}(\psi - 0)$

Since λ_2 is the correlation coefficient between the hazard job random effect and the wage job random effect, it is equal to the covariance of these two effects divided by the standard deviation of each individual effect. I normalize the variance of the hazard job random effect to one since it is not identified and treat λ_2 as the covariance divided by the standard deviation of ψ.

is some evidence that the effect of employer-provided health insurance depends upon the type of insurance. For example, workers who pay all of their health insurance premiums without any employer contributions experience essentially no job-lock.

In the wage model, tenure is determined to be a significant predictor of wages. My estimates of 1.5%-2% per year after the first four years are slightly higher than the low estimates of Abraham and Farber and Altonji and Shakotko but lower than those of Topel. Heterogeneity seems to be the main cause for biased returns to seniority as the joint estimation of the tenure and wage equations did not reduce the tenure coefficients substantially more than had been caused by the inclusion of person and job heterogeneity.

The correlation coefficients from the joint estimation of the full three equation model provide support for the idea that wages, health benefits, and job tenure are three jointly determined outcomes. A job which pays a 5% log wage premium is 6% less likely to end all else equal. In comparison, a job which has a 73% probability of providing health insurance compared to an observationally equivalent job with a 60% probability, is also approximately 6% less likely to end. The monetary costs to the employer of these equivalent reductions in mobility are very different. The increase in the probability of family coverage health insurance represents a $564 gain in expected annual compensation while the 5% log wage premium represents a $882 increase in take-home pay. Health insurance appears to be worth more to workers than the equivalent amount of wages. These results point to the need for further studies of the wage/benefit trade-off using more detailed microdata on the cost of health insurance to the worker and the firm. Given the possibility that the health insurance market in the United States may move towards an individual plan-based system where firms subsidize but do not provide health insurance, employers will increasingly consider how much additional direct compensation is necessary in order to make a worker willing to give up health benefits and still remain relatively stable.

The relationship between the composition of benefit packages and tenure is also important when studying firms and the choices they make about what kind of workers to employ. Some firms may choose to pay average wages, provide no benefits, and experience high turnover rates. This type of business strategy would avoid the costs associated with job-lock. However, other kinds of firms may desire a more stable workforce and hence will have a cost incentive to increase the benefits/wages ratio. In making this decision, the firm will have to balance the efficiency loss due to job-lock with the gains from stability. By studying firm outcomes such as productivity per worker and sales per worker and how these relate to compensation packages and turnover rates, one could assess the efficiency gains and losses associated with high or low turnover and study how firms make these choices in order to profit maximize.

References

[1] Abowd, John M., Francis Kramarz, David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, March 1999, 251-333.

[2] Abraham, Katharine G. and Henry S. Farber, "Job Duration, Seniority, and Earnings," *The American Economic Review*, June 1987, 278-297.

[3] Altonji, Joseph G. and Robert A. Shakotko, "Do Wages Rise with Job Seniority," *The Review of Economic Studies*, July 1987, 437-459.

[4] Branscome, James M. and Erwin Brown, Jr., "State Differences in Job-Related Health Insurance 1998," Agency for Healthcare Research and Quality, Publication No. 01-0036, 2001.

[5] Buchmueller, Thomas C. and Robert G. Valletta, "The Effects of Employer-Provided Health Insurance on Worker Mobility," *Industrial and Labor Relations Review*, April 1996, 439-455.

[6] Dostie, Benoit, "A Study of the Impact of Sales Shocks and Job Matching on Wages, Turnover, and Returns to Seniority," unpublished manuscript, Cornell University, 2001;

[7] Gilleskie, Donna B. and Byron F. Lutz, "The Impact of Employer-Provided Health Insurance on Dynamic Employment Transitions," NBER Working Paper No. 7307, 1999.

[8] Kapur, Kanika, "The Impact of Health on Job Mobility: A Measure of Job Lock," *Industrial and labor Relations Review*, Jan 1998, 282-298.

[9] Lillard, Lee A., "Job Turnover Heterogeneity and Person-Job-Specific Time-Series Wages," in Econometrics of Panel Data, Special issue of "Annales d'Économie et de Statistique," 1999 No. 55-56, 183-210.

[10] Lillard, Lee A. and Constantijn W.A. Panis, aML Multilevel Multiprocess Statistical Software User's Guide and Reference Manual, Release 1.0, 2000, EconWare, Los Angeles, California.

[11] Madrian, Brigitte C., "Employment-Based Health Insurance and Job Mobility: Is There Evidence of Job-Lock?" *The Quarterly Journal of Economics*, Feb 1994, 27-54.

[12] Monheit, Alan C. and Philip F. Cooper, "Health Insurance and Job Mobility: Theory and Evidence," *Industrial and Labor Relations Review*, Oct 1994, 68-85.

[13] Searle, Shayle R., George Casella, Charles E. McCulloch, Variance Components, John Wiley & Sons, Inc., 1992, 315-366.

[14] Topel, Robert H. and Michael P. Ward, "Job Mobility and the Careers of Young Men," *Quarterly Journal of Econometrics*, 1992, 439-479.

[15] Topel, Robert H., "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority." *Journal of Political Economy,* Feb 1991.

Table 1a

Summary Statistics for Individuals 1996 SIPP Panel*							
Time-Invariant Person Char				Time Varying Person Char: Workers in 1996:3			
Variable	N	Mean	Std. Dev.	Variable	N	Mean	Std. Dev.
white (%)	35,060	84.31		married (%)	24,639	61.72	
years of education	35,060	13.03	2.701	kids	24,639	0.98	1.160
no high school degree (%)	35,060	15.85		kids < 18 years old	24,639	0.82	1.092
high school degree (%)	35,060	29.37		HI coverage (%)	24,639	84.69	
some college (%)	35,060	31.35		HI own name(%)	24,639	65.72	
college degree (%)	35,060	16.09		HI employer (%)	24,639	60.25	
graduate degree (%)	35,060	7.33		HI military (%)	24,639	0.47	
male (%)	35,060	49.31		HI previous employer (%)	24,639	1.56	
Hispanic (%)	35,060	9.86		HI private (%)	24,639	3.44	
number of jobs	35,060	1.98	1.324	HI other person's name (%)	24,639	24.06	
chronic,non-severe health condition (%)	35,060	14.12		HI both own and other (%)	24,639	5.08	
				Time Varying Person Char: Workers in 1999:3			
				Variable	N	Mean	Std. Dev.
				married (%)	19,937	62.41	
				kids	19,937	1.04	1.192
				kids < 18 years old	19,937	0.84	1.109
				HI coverage (%)	19,937	87.26	
				HI own name(%)	19,937	67.16	
				HI employer (%)	19,937	62.17	
				HI military (%)	19,937	0.52	
				HI previous employer (%)	19,937	1.55	
				HI private (%)	19,937	2.92	
				HI other person's name (%)	19,937	26.26	
				HI both own and other (%)	19,937	6.17	

*Includes original sample members of the 1996 SIPP Panel who were not active duty military at any point during the panel. In addition respondents must have held at least one job that 1) began after age 18, 2) either ended or was censored before age 60, 3) was on-going at some point during the period 1995:12 and 2000:2, 4) had total earnings > 0, 5) had at least one month with a non-imputed hourly wage >= $.1, 6) had job duration > 1 day, 7) a non-family employer. All statistics are weighted.

Table 1b

Summary Statistics for Jobs 1996 SIPP Panel

Time-Invariant Job Characteristics

	Variable	N	Mean	Std. Dev.
Job Duration (months)		69,331	48.01	75.439
Number of months observed		69,331	15.74	14.816
Job Censored (%)		69,331	41.40	
Labor Force Exp begin job (months)		69,331	155.72	117.414
Age begin job (years)		69,331	31.09	10.010
Union/Covered by Union (%)		69,331	14.22	
Industry	Agriculture (%)	69,331	1.83	
	Mining (%)	69,331	0.42	
	Construction (%)	69,331	5.84	
	Manufacturing (%)	69,331	14.31	
	Transport., Comm.,Public Util. (%)	69,331	6.09	
	Wholesale Trade (%)	69,331	3.58	
	Retail Trade (%)	69,331	20.12	
	FIRE (%)	69,331	5.43	
	Services (%)	69,331	37.97	
	Public Admin (%)	69,331	4.41	
Job type	Private, For-Profit (%)	69,331	79.77	
	Private, Not-for-Profit (%)	69,331	6.96	
	Local Govt (%)	69,331	6.67	
	State Govt (%)	69,331	4.40	
	Federal Govt (%)	69,331	2.21	

Time-Varying Job Characteristics in 1996:3

Variable	N	Mean	Std. Dev.
real hourly wage ($ 1999)	25,488	15.01	17.316
hours per week	25,488	39.36	12.288
Employer-provided HI (%)	25,488	58.82	

Time-Varying Job Characteristics in 1999:3

Variable	N	Mean	Std. Dev.
real hourly wage ($ 1999)	20,980	14.34	19.993
hours per week	20,980	38.49	12.190
Employer-provided HI (%)	20,980	59.33	

Table 2a

Summary Statistics for Individuals 1990 SIPP Panel*							
Time-Invariant Person Char				Time Varying Person Char: Workers in 1990:3			
Variable	N	Mean	Std. Dev.	Variable	N	Mean	Std. Dev.
white (%)	18,634	85.27		married (%)	14,644	61.64	
years of education	18,634	13.06	2.699	kids	14,644	0.99	1.180
no high school degree (%)	18,634	16.57		kids < 18 years old	14,644	0.81	1.091
high school degree (%)	18,634	34.51		HI coverage (%)	14,644	87.23	
some college (%)	18,634	27.57		HI own name(%)	14,644	69.53	
college degree (%)	18,634	10.40		HI employer (%)	14,644	64.40	
graduate degree (%)	18,634	10.95		HI military (%)	14,644	0.50	
male (%)	18,634	50.02		HI previous employer (%)	14,644	1.13	
Hispanic (%)	18,634	7.68		HI private (%)	14,644	3.50	
number of jobs	18,634	1.78	1.133	HI other person's name (%)	14,644	21.21	
chronic,non-severe health condition (%)	18,634	8.65		HI both own and other (%)	14,644	3.51	
				Time Varying Person Char: Workers in 1992:3			
				Variable	N	Mean	Std. Dev.
				married (%)	14,661	62.01	
				kids	14,661	1.00	1.179
				kids < 18 years old	14,661	0.80	1.097
				HI coverage (%)	14,661	87.27	
				HI own name(%)	14,661	69.51	
				HI employer (%)	14,661	64.68	
				HI military (%)	14,661	0.58	
				HI previous employer (%)	14,661	1.11	
				HI private (%)	14,661	3.14	
				HI other person's name (%)	14,661	21.51	
				HI both own and other (%)	14,661	3.74	

*Includes original sample members of the 1990 SIPP Panel who were not active duty military at any point during the panel. In addition respondents must have held at least one job that 1) began after age 18, 2) either ended or was censored before age 60, 3) was on-going at some point during the period 1989:10 and 1992:8, 4) had total earnings > 0, 5) had at least one month with a non-imputed hourly wage >= $.1, 6) had job duration > 1 day, 7) a non-family employer. All statistics are weighted.

Table 2b

Summary Statistics for Jobs 1990 SIPP Panel

Time-Invariant Job Characteristics				
Variable		N	Mean	Std. Dev.
Job Duration (months)		32,623	48.33	74.336
Number of months observed		32,623	14.74	11.550
Job Censored (%)		32,623	50.52	
Labor Force Exp begin job (months)		32,623	126.55	115.302
Age begin job (years)		32,623	30.59	9.974
Union/Covered by Union (%)		32,623	17.02	
Industry	Agriculture (%)	32,623	1.95	
	Mining (%)	32,623	0.47	
	Construction (%)	32,623	5.89	
	Manufacturing (%)	32,623	16.56	
	Transport., Comm.,Public Util. (%)	32,623	6.75	
	Wholesale Trade (%)	32,623	3.71	
	Retail Trade (%)	32,623	19.31	
	FIRE (%)	32,623	5.53	
	Services (%)	32,623	35.24	
	Public Admin (%)	32,623	4.58	
Job type	Private, For-Profit (%)	32,623	80.69	
	Private, Not-for-Profit (%)	32,623	5.13	
	Local Govt (%)	32,623	2.69	
	State Govt (%)	32,623	4.51	
	Federal Govt (%)	32,623	6.98	

Time-Varying Job Characteristics in 1990:3			
Variable	N	Mean	Std. Dev.
real hourly wage ($ 1999)	15,288	14.26	10.875
hours per week	15,288	38.55	11.624
Employer-provided HI (%)	15,288	62.29	

Time-Varying Job Characteristics in 1992:3			
Variable	N	Mean	Std. Dev.
real hourly wage ($ 1999)	15,262	14.07	12.275
hours per week	15,262	37.88	11.392
Employer-provided HI (%)	15,262	62.35	

Figure 1

Breakdown of changes in Employer-Provided Health Insurance within Job: 1996 SIPP

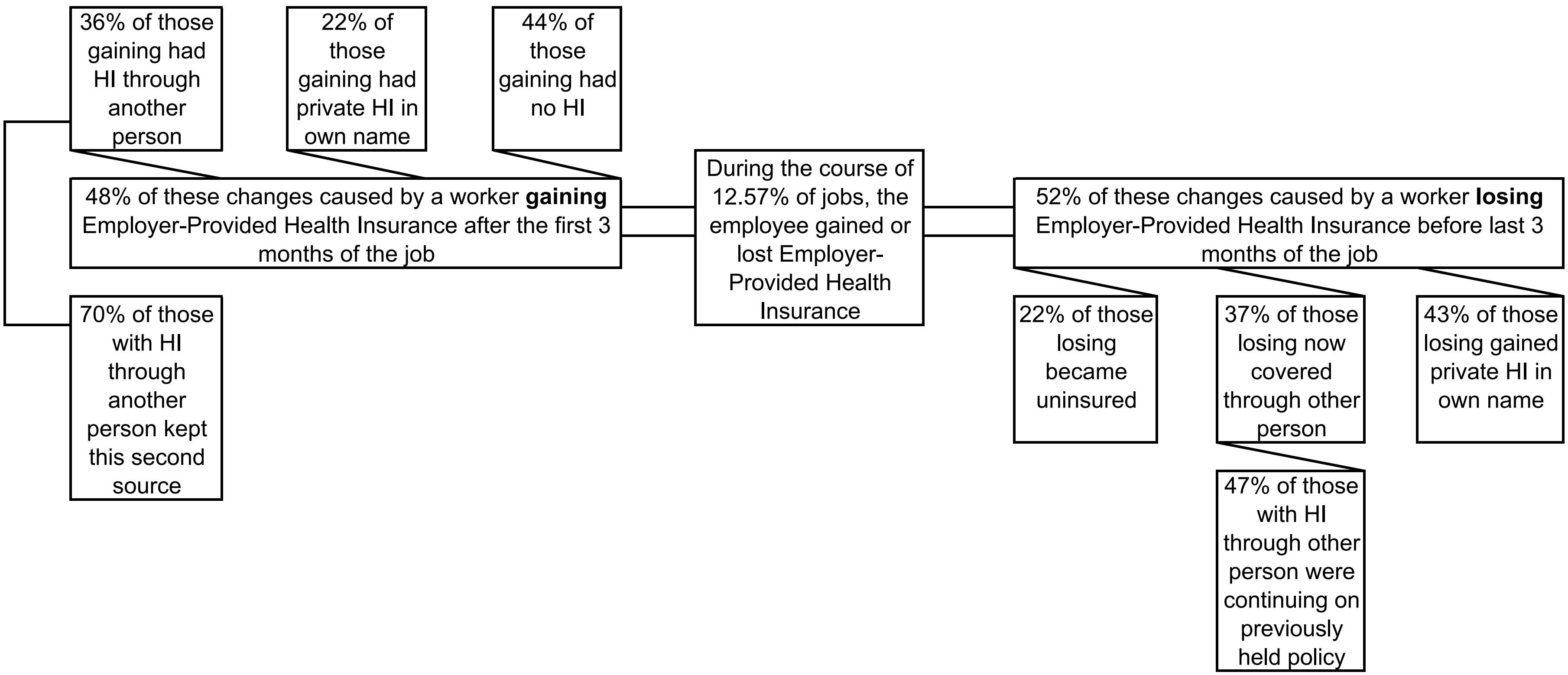

Figure 2

Breakdown of changes in Employer-Provided Health Insurance within Job: 1990 SIPP

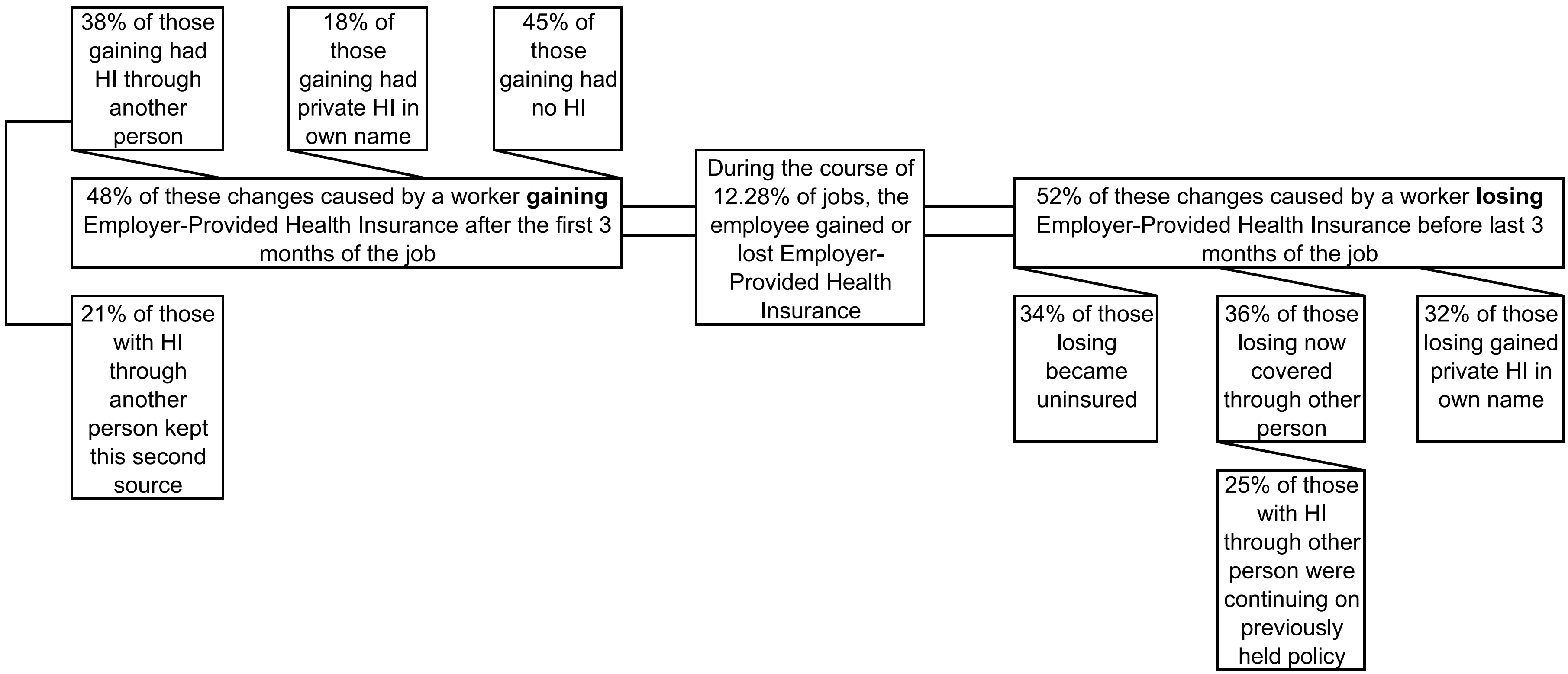

Table 3

Joint Hazard, Health Insurance Specification: 1996 SIPP				
	(1)	(2)	(3)	(4)
	no heterogeneity	person heterogeneity	correlated person heterogeneity	correlated person heterogeneity, job heterogeneity
Hazard Ratios for Health Insurance Indicators: married, male baseline				
HIEMPLOYER	0.347	0.309	0.357	0.444
	(0.0250)***	(0.0282)***	(0.0253)***	(0.0274)***
HIOTHER	0.719	0.701	0.718	0.716
	(0.0270)***	(0.0320)***	(0.0276)***	(0.0284)***
BOTH	0.488	0.452	0.500	0.613
	(0.0499)***	(0.0537)***	(0.0868)***	(0.0517)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.680	0.743	0.679	0.671
Standard Deviations and Correlation Coefficients of Random Effects				
σ_δ		0.5324 ***	0.1624 ***	0.2587 ***
$\rho_{\delta\gamma}$			-0.2182 ***	-0.2166 ***
λ_1				-0.0771 ***
Other Person Characteristics: Hazard Ratios				
Own HI, not HIEMP	1.072	1.139	1.088	1.086
	(0.0144)***	(0.0170)***	(0.0147)***	(0.0153)***
white	0.979	0.958	0.975	0.965
	(0.0124)*	(0.0169)**	(0.0128)**	(0.0136)***
hispanic	0.912	0.914	0.915	0.918
	(0.0156)***	(0.0210)***	(0.0161)***	(0.0170)***
high school degree	1.018	1.008	1.008	0.980
	(0.0139)	(0.0192)	(0.0144)	(0.0154)
some college	1.070	1.064	1.062	1.031
	(0.0143)***	(0.0196)***	(0.0148)***	(0.0158)*
college degree	1.038	1.027	1.021	0.953
	(0.0190)*	(0.0251)	(0.0195)	(0.0207)**
graduate degree	0.968	0.948	0.953	0.884
	(0.0267)	(0.0341)	(0.0274)*	(0.0287)***
male	0.926	0.910	0.923	0.914
	(0.0169)***	(0.0227)***	(0.0175)***	(0.0185)***
married	0.957	0.950	0.963	0.967
	(0.0208)**	(0.0261)*	(0.0214)*	(0.0224)
number of kids=1	0.979	0.980	0.980	0.982
	(0.0061)***	(0.0079)***	(0.0063)***	(0.0066)***
baseline hazard	0.030	0.031	0.029	0.025

Note: In addition to reported controls, the hazard equation was estimated with piecewise linear splines in age, calendar time, labor force experience, and tenure and controls for union status, industry, and job type. Gender and marital status were interacted with the health insurance variables so these hazard ratios are group-specific; hazard ratio-1= percentage change in the probability of leaving a job; standard errors are in parantheses; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3a

Joint Hazard, Health Insurance Specification: 1996 SIPP				
	(1)	(2)	(3)	(4)
	no heterogeneity	person heterogeneity	correlated person heterogeneity	correlated person heterogeneity, job heterogeneity
Hazard Ratios for Health Insurance Indicators: single, male baseline				
HIEMPLOYER	0.371	0.335	0.380	0.470
	(0.0253)***	(0.0280)***	(0.0257)***	(0.0277)***
HIOTHER	1.119	1.168	1.128	1.141
	(0.0237)***	(0.0301)***	(0.0245)***	(0.0259)***
BOTH	0.510	0.498	0.528	0.662
	(0.0910)***	(0.09437)***	(0.0918)***	(0.0934)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.165	0.183	0.166	0.165

Hazard Ratios for Health Insurance Indicators: married, female baseline				
HIEMPLOYER	0.305	0.265	0.312	0.386
	(0.0321)***	(0.0352)***	(0.0324)***	(0.0345)***
HIOTHER	0.660	0.628	0.652	0.646
	(0.0223)***	(0.0267)***	(0.0227)***	(0.0236)***
BOTH	0.450	0.403	0.461	0.561
	(0.0434)***	(0.0465)***	(0.04387)***	(0.04548)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.838		0.856	0.860

Hazard Ratios for Health Insurance Indicators: single, female baseline				
HIEMPLOYER	0.329	0.288	0.336	0.417
	(0.0257)***	(0.0280)***	(0.0260)***	(0.0281)***
HIOTHER	0.944	0.952	0.949	0.953
	(0.0236)**	(0.0296)***	(0.0243)**	(0.0257)**
BOTH	0.471	0.426	0.481	0.606
	(0.1022)***	(0.1095)***	(0.1034)***	(0.1057)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.361	0.375	0.356	0.361

Note: In addition to reported controls, the hazard equation was estimated with piecewise linear splines in age, calendar time, labor force experience, and tenure and controls for union status, industry, and job type. Gender and marital status were interacted with the health insurance variables so these hazard ratios are group-specific; hazard ratio-1= percentage change in the probability of leaving a job; standard errors are in parantheses; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure 3
Hazard of Job Ending
Married Men 1996 SIPP

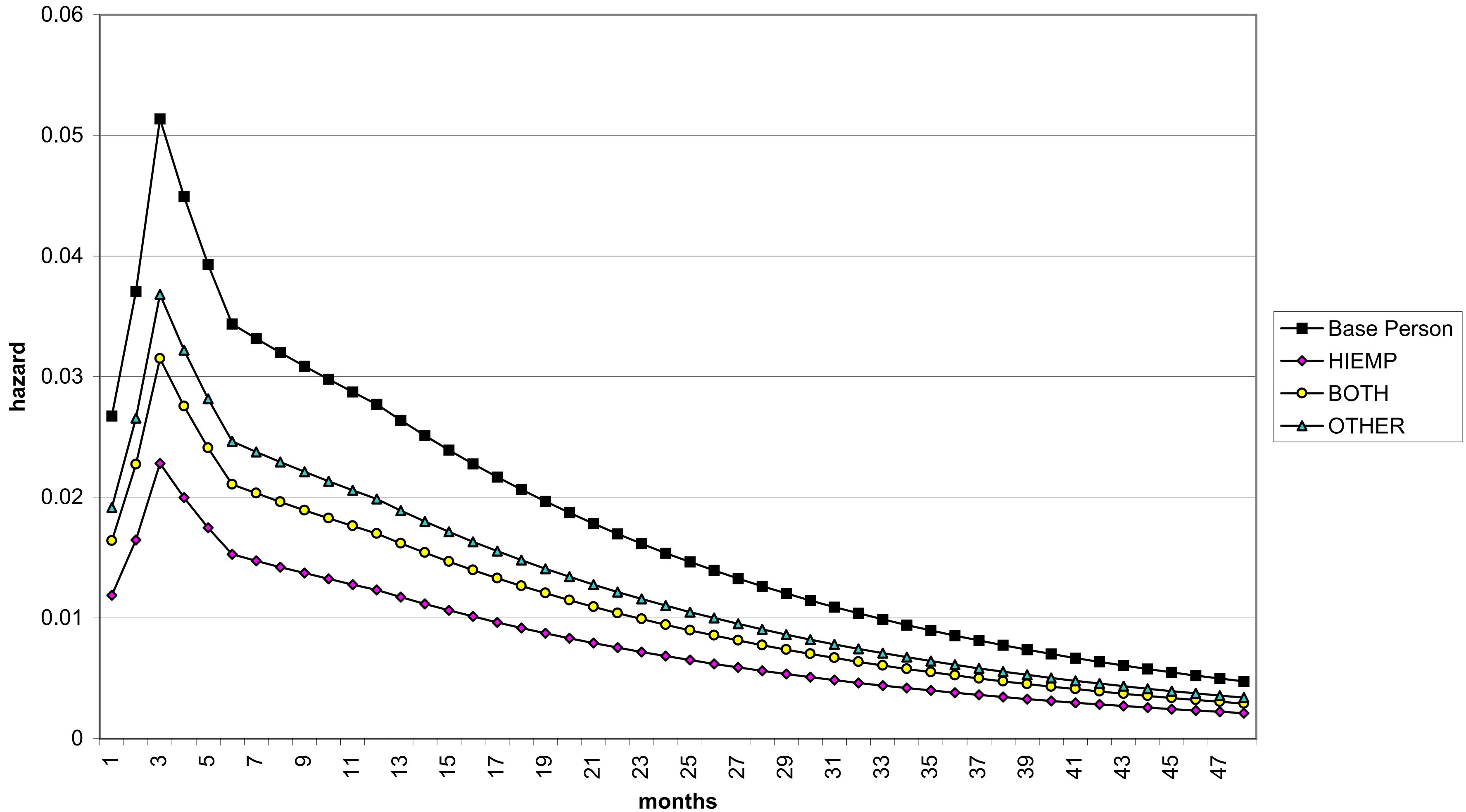

Table 4

Probability of Having Employer Provided Health Insurance: 1996 SIPP				
	(1)	(2)	(3)	(4)
	no heterogeneity	person heterogeneity	correlated person heterogeneity	correlated person heterogeneity, job heterogeneity
Standard Deviations of Random Effects				
σ_γ		3.7016 ***	4.2883 ***	4.2908 ***
σ_ε		2.6341 ***	2.6890 ***	2.6945 ***
Person and Job Characteristics				
constant	-1.5854 ***	-3.1779 ***	-2.6347 ***	-2.6269 ***
	(0.0030)	(0.0249)	(0.0289)	(0.0282)
white	0.1255 ***	0.6957 ***	0.4821 ***	0.4713 ***
	(0.0008)	(0.0090)	(0.0114)	(0.0111)
high school degree	0.4208 ***	2.2608 ***	2.2869 ***	2.2249 ***
	(0.0010)	(0.0129)	(0.0152)	(0.0149)
some college	0.5374 ***	2.6391 ***	2.2103 ***	2.1870 ***
	(0.0010)	(0.0135)	(0.0151)	(0.0148)
college degree	0.8192 ***	4.0325 ***	4.4633 ***	4.4732 ***
	(0.0011)	(0.0172)	(0.0208)	(0.0203)
graduate degree	0.9663 ***	4.7017 ***	4.4751 ***	4.4564 ***
	(0.0014)	(0.0213)	(0.0250)	(0.0243)
hispanic	-0.1307 ***	-1.0825 ***	-0.4523 ***	-0.4932 ***
	(0.0009)	(0.0107)	(0.0133)	(0.0128)
male	-0.1492 ***	0.9382 ***	0.7945 ***	0.7868 ***
	(0.0010)	(0.0101)	(0.0122)	(0.0119)
chronic, non-severe health condition	-0.0166 ***	-0.4902 ***	-0.2417 ***	-0.2333 ***
	(0.0008)	(0.0095)	(0.0116)	(0.0113)
number of kids	-0.0999 ***	-0.1609 ***	-0.1285 ***	-0.1235 ***
	(0.0003)	(0.0031)	(0.0037)	(0.0037)
married	-0.3155 ***	-0.7586 ***	-0.6177 ***	-0.6261 ***
	(0.0009)	(0.0068)	(0.0076)	(0.0075)
male*married	0.4716 ***	0.6042 ***	0.5229 ***	0.5354 ***
	(0.0013)	(0.0106)	(0.0117)	(0.0115)
male*kids	0.1204 ***	0.3650 ***	0.2868 ***	0.2786 ***
	(0.0005)	(0.0047)	(0.0054)	(0.0053)
weekly hours > 20	1.8466 ***	1.3806 ***	1.3070 ***	1.2989 ***
	(0.0022)	(0.0086)	(0.0089)	(0.0089)
age beginning of job	-0.0093 ***	-0.0533 ***	-0.0550 ***	-0.0543 ***
	(0.0000)	(0.0004)	(0.0004)	(0.0004)
union	1.8466 ***	1.3806 ***	1.3070 ***	1.2989 ***
	(0.0022)	(0.0086)	(0.0089)	(0.0089)

Note: In addition to reported controls, the probit equation was estimated with controls for industry and job type; standard errors are in parantheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level; excluded category=female, no high school degree, non-white, non-Hispanic, non-married, non-union,wholesale trade industry, private-for-profit employer

Table 5

Joint Hazard, Health Insurance Specification: 1990 SIPP				
	(1)	(2)	(3)	(4)
	no heterogeneity	person heterogeneity	correlated person heterogeneity	correlated person heterogeneity, job heterogeneity
Standard Deviations and Correlation Coefficients of Random Effects				
σ_δ		0.3640 ***	0.3252 ***	0.3505 ***
$\rho_{\delta\gamma}$			-0.2179 ***	-0.2216 ***
λ_1				-0.0467 ***
Hazard Ratios for Health Insurance Indicators: married, male baseline				
HIEMPLOYER	0.380	0.368	0.403	0.472
	(0.0387)***	(0.0410)***	(0.0408)***	(0.0458)***
HIOTHER	0.774	0.772	0.764	0.765
	(0.0480)***	(0.0522)***	(0.0517)***	(0.0522)***
BOTH	0.555	0.538	0.581	0.680
	(0.0908)***	(0.0945)***	(0.0946)***	(0.0972)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.607	0.611	0.617	0.613

Hazard Ratios for Health Insurance Indicators: single, male baseline				
HIEMPLOYER	0.391	0.377	0.409	0.477
	(0.0390)***	(0.04136)***	(0.0409)***	(0.0463)***
HIOTHER	0.967	0.985	0.975	0.977
	(0.0395)	(0.0453)	(0.0444)	(0.0450)
BOTH	0.731	0.749	0.790	0.947
	(0.2655)	(0.2703)	(0.2722)	(0.2732)
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.499		0.509	0.520

Hazard Ratios for Health Insurance Indicators: married, female baseline				
HIEMPLOYER	0.342	0.326	0.356	0.415
	(0.0508)***	(0.0533)***	(0.0527)***	(0.0566)***
HIOTHER	0.699	0.689	0.684	0.682
	(0.0379)***	(0.04128)***	(0.0405)***	(0.0410)***
BOTH	0.563	0.547	0.592	0.689
	(0.0807)***	(0.0838)***	(0.0831)***	(0.0861)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.823	0.856	0.860	0.864

Hazard Ratios for Health Insurance Indicators: single, female baseline				
HIEMPLOYER	0.337	0.322	0.351	0.413
	(0.0413)***	(0.0433)***	(0.0427)***	(0.0480)***
HIOTHER	0.970	0.986	0.978	0.979
	(0.0389)	(0.0435)	(0.0425)	(0.0433)
BOTH	0.880	0.886	0.951	1.126
	(0.1973)	(0.2026)	(0.2037)	(0.2060)
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER				
	0.648	0.651	0.654	0.655

Note: In addition to reported controls, the hazard equation was estimated with piecewise linear splines in age, calendar time, labor force experience, and tenure and controls for union status, industry, and job type. Gender and marital status were interacted with the health insurance variables so these hazard ratios are group-specific; hazard ratio-1= percentage change in the probability of leaving a job; standard errors are in parantheses; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6

Joint Hazard, Health Insurance Specification: 1996 SIPP		
Health Insurance Coverage Types: single, single+1, multiple		
	(1)	(2)
	correlated person heterogeneity	correlated person heterogeneity, job heterogeneity
Standard Deviations and Correlation Coefficients of Random Effects		
σ_δ	0.1505 ***	0.2528 ***
$\rho_{\delta\gamma}$	-0.2183 ***	-0.2168 ***
λ_1		-0.0776 ***
Hazard Ratios for Health Insurance Indicators: HIEMP covers worker only		
HIEMPLOYER	0.377	0.470
	(0.0176)***	(0.0204)***
HIOTHER	0.815	0.813
	(0.0132)***	(0.0138)***
BOTH	0.622	0.770
	(.0405)***	(.0420)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER		
	0.620	0.619
Hazard Ratios for Health Insurance Indicators: HIEMP covers worker + 1 family member		
HIEMPLOYER	0.347	0.432
	(0.0286)***	(0.0304)***
HIOTHER	0.815	0.813
	(0.0132)***	(0.0138)***
BOTH	0.438	0.540
	(.0769)***	(.0662)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER		
	0.436	0.430
Hazard Ratios for Health Insurance Indicators: HIEMP covers worker + >1 family members		
HIEMPLOYER	0.329	0.409
	(0.0238)***	(.0259)***
HIOTHER	0.815	0.813
	(0.0132)***	(0.0138)***
BOTH	0.372	0.455
	(.0647)***	(.0619)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER		
	0.341	0.331

Note: In addition to reported controls, the hazard equation was estimated with piecewise linear splines in age, calendar time, labor force experience, and tenure and controls for union status, industry, and job type; hazard ratio-1= percentage change in the probability of leaving a job; standard errors are in parantheses; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 7

Joint Hazard, Health Insurance Specification: 1996 SIPP		
Health Insurance Coverage Types: worker pays all, part, or none of premiums		
	(1)	(2)
	correlated person heterogeneity	correlated person heterogeneity, job heterogeneity
Standard Deviations and Correlation Coefficients of Random Effects		
σ_δ	0.1522 ***	0.2641 ***
$\rho_{\delta\gamma}$	-0.2182 ***	-0.2165 ***
λ_1		-0.0844 ***
Hazard Ratios for Health Insurance Indicators: Worker pays no HIEMP costs		
HIEMPLOYER	0.348	0.440
	(0.0224)***	(0.0246)***
HIOTHER	0.816	0.813
	(0.0131)***	(0.0138)***
BOTH	0.371	0.463
	(.0601)***	(.0566)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER		
	0.290	0.280
Hazard Ratios for Health Insurance Indicators: Worker pays part of HIEMP costs		
HIEMPLOYER	0.317	0.400
	(0.0174)***	(0.0200)***
HIOTHER	0.816	0.813
	(0.0131)***	(0.0138)***
BOTH	0.387	0.481
	(.0474)***	(.0640)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER		
	0.408	0.400
Hazard Ratios for Health Insurance Indicators: Worker pays all of HIEMP costs		
HIEMPLOYER	0.637	0.808
	(0.0420)***	(.0437)***
HIOTHER	0.816	0.813
	(0.0131)***	(0.0138)***
BOTH	0.344	0.422
	(.0603)***	(.0960)***
Difference-in-Difference: (BOTH-HIEMP)/BOTH - (HIOTHER-1)/HIOTHER		
	-0.628	-0.684

Note: In addition to reported controls, the hazard equation was estimated with piecewise linear splines in age, calendar time, labor force experience, and tenure and controls for union status, industry, and job type; hazard ratio-1= percentage change in the probability of leaving a job; standard errors are in parantheses; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 8

Joint Hazard, Health Insurance Specification: 1996 SIPP		
Wave 5 Jobs: offer versus take-up; person heterogeneity from full model		
	Hazard Ratio	Standard Error
Eligible for HIEMP	0.523	(0.043)***
Eligible for and Have HIEMP	0.384	(0.044)***
Have HIOTHER	0.966	(0.037)
Difference: (Have HIEMP-Eligible for HIEMP)/Have HIEMP		
	-0.361	

Note: In addition to reported controls, the hazard equation was estimated with piecewise linear splines in age, calendar time, labor force experience, and tenure and controls for union status, industry, and job type; hazard ratio-1= percentage change in the probability of leaving a job; standard errors are in parantheses; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 9

Joint Wage, Hazard Specification: 1996 SIPP				
	(1)	(2)	(3)	(4)
	no heterogeneity	person and job heterogeneity	correlated person heterogeneity	correlated person and job heterogeneity
σ_η	0.4836 ***	0.2488 ***	0.2488 ***	0.2488 ***
σ_θ		0.3064 ***	0.3064 ***	0.3069 ***
σ_ψ		0.3375 ***	0.3374 ***	0.3375 ***
σ_δ			0.5342 ***	0.5456 ***
$\rho_{\delta\theta}$			-0.0260 *	0.1647 ***
λ_2				-0.5299 ***
Person Characteristics				
tenure 0-3 months	-0.0040 **	-0.0111 ***	-0.0112 ***	-0.0117 ***
	(0.0017)	(0.0007)	(0.0007)	(0.0007)
tenure 3-6 months	0.0062 ***	0.0028 ***	0.0028 ***	0.0027 ***
	(0.0010)	(0.0004)	(0.0004)	(0.0004)
tenure 6-12 months	0.0059 ***	0.0031 ***	0.0031 ***	0.0032 ***
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
tenure 12-48 months	0.0022 ***	0.0023 ***	0.0023 ***	0.0025 ***
	(0.00002)	(.00003)	(0.00003)	(0.00003)
tenure 48-120 months	0.0018 ***	0.0012 ***	0.0012 ***	0.0013 ***
	(0.000007)	(.00003)	(0.00003)	(0.00002)
tenure 120+ months	0.0008 ***	0.0006 ***	0.0006 ***	0.0007 ***
	(0.000003)	(.00003)	(0.00003)	(0.00003)
white	0.0662 ***	0.0676 ***	0.0676 ***	0.0666 ***
	(0.0003)	(.0064)	(0.0064)	(0.0064)
high school degree	0.1480 ***	0.1216 ***	0.1218 ***	0.1204 ***
	(0.0004)	(.0082)	(0.0082)	(0.0082)
some college	0.3113 ***	0.2752 ***	0.2753 ***	0.2744 ***
	(0.0004)	(.0079)	(0.0079)	(0.0079)
college degree	0.6087 ***	0.5809 ***	0.5810 ***	0.5806 ***
	(0.0004)	(0.0084)	(0.0084)	(0.0084)
graduate degree	0.8378 ***	0.8277 ***	0.8279 ***	0.8272 ***
	(0.0005)	(0.0097)	(0.0098)	(0.0098)
hispanic	-0.0828 ***	-0.0736 ***	-0.0736 ***	-0.0731 ***
	(0.0004)	(0.0081)	(0.0081)	(0.0081)
male	0.0803 ***	0.1368 ***	0.1368 ***	0.1363 ***
	(0.0003)	(0.0048)	(0.0048)	(0.0048)
experience 0-12 months	-0.0055 ***	0.0004	0.0004	-0.0003
	(0.0011)	(0.0008)	(0.0008)	(0.0008)
experience 12-24 months	0.0066 ***	0.0049 ***	0.0049 ***	0.0047 ***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
experience 24-60 months	0.0010 ***	0.0024 ***	0.0024 ***	0.0023 ***
	(0.00004)	(0.0001)	(0.0001)	(0.0001)
experience 60-120 months	0.0012 ***	0.0018 ***	0.0018 ***	0.0018 ***
	(0.00001)	(0.00003)	(0.00003)	(0.00003)
experience 120-240 months	0.0010 ***	0.0010 ***	0.0010 ***	0.0010 ***
	(0.000003)	(0.00002)	(0.00002)	(0.00002)
experience 240+ months	-0.0001 ***	-0.0001 ***	-0.0001***	-0.0001***
	(0.000001)	(0.00002)	(0.00002)	(0.00002)

Note: Dependent variable is real monthly wages; In addition to reported controls, the wage equation was estimated with continuous calendar time and controls for marital status, number of kids, interactions of gender, marital status, and number of kids, union status, industry, and job type. Wages are in 1999 dollar terms; standard errors are in parantheses; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level; excluded category=female, no high school degree, non-white, non-Hispanic, non-married, non-union,wholesale trade industry, private-for-profit employer.

Table 10

Joint Hazard, Health Insurance, and Wage Specification		
	1990 SIPP	1996 SIPP
Random Effects: Standard Deviations and Correlations		
σ_{δ}	0.4422 ***	0.6204 ***
σ_{θ}	0.3311 ***	0.3224 ***
σ_{γ}	5.9019 ***	5.9472 ***
$\rho_{\delta\theta}$	-0.2174 ***	0.1289 ***
$\rho_{\delta\gamma}$	-0.5032 ***	-0.3961 ***
$\rho_{\theta\gamma}$	0.5221 ***	0.3555 ***
σ_{ψ}	0.3007 ***	0.3501 ***
σ_{ε}	4.6753 ***	4.9401 ***
$\rho_{\psi\varepsilon}$	0.3111 ***	0.3556 ***
λ_1	-0.0609 ***	-0.0920 ***
λ_2	0.0120	-0.4139 ***
σ_{η}	0.2333 ***	0.2487 ***
Wage Equation: Tenure Coefficients		
tenure 0-3 months	-0.0017	-0.0122
	(0.0011)	(0.0007)***
tenure 3-6 months	0.0048	0.0028
	(0.0006)***	(0.0004)***
tenure 6-12 months	0.0015	0.0040
	(0.0002)***	(0.0001)***
tenure 12-48 months	0.0017	0.0031
	(0.00005)***	(0.00003)***
tenure 48-120 months	0.0005	0.0016
	(0.00004)***	(0.00002)***
tenure 120+ months	0.0003	0.0009
	(0.00004)***	(0.00002)***
Hazard Ratios for Health Insurance Variables		
HIEMPLOYER	0.580	0.640
	(0.0377)***	(0.0226)***
HIOTHER	0.803	0.779
	(0.0245)***	(0.0164)***
BOTH	0.954	0.888
	(.0650)***	(0.0358)***
Difference-in-Difference	0.638	0.563

Note: Preliminary results; joint hazard, health insurance, wage equations were estimated with controls for male, white, Hispanic, marital status, number of kids, interactions of kids and marital status with male, education levels, union status; hazard equation contained piecewise linear splines in age, tenure, labor force experience, and calendar time; wage equation contained spline in tenure coefficients and general labor market experience; health insurance equation contained age at beginning of job, health condition indicator, and hours worked per week; * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level;