The Effect of Employer-Provided Health Insurance on Job Mobility: Job-Lock or Job-Push?

Patricia M. Anderson
Department of Economics
Dartmouth College
and NBER
[patty.anderson@dartmouth.edu]

May 1997

This project was funded by the U.S. Department of Labor, Bureau of Labor Statistics under grant number E-9-J-4-0094. Opinions and conclusions expressed in this document are those of the author and do not necessarily represent an official position of the Bureau of Labor Statistics or the U.S. Department of Labor.
Abstract

This paper analyzes the impact of employer-provided health insurance on individual job mobility. Much attention has been paid in recent years to the problem of job-lock, in which workers are locked into jobs they would otherwise leave because of fear of losing health insurance. Much less attention has been paid to the parallel case in which a worker in need of coverage is pushed out of a job in which they would otherwise remain, a phenomenon I refer to as “job-push.” I use a sample of job spells from the Youth panel of the National Longitudinal Survey (NLS-Y) to estimate a proportional hazard model where health insurance coverage, along with other key covariates, is treated as time-varying. Additionally, I estimate probit models using more detailed information on health coverage than has typically been available. I find overall mobility effects in the range of past studies - about 20 to 40 percent, but I conclude that as much as one half of this effect may be better categorized as job-push. This distinction is important, because policy reforms directed at job-lock may have no effect on job-push, and may possibly even worsen the problem.
I. Introduction

According to Census Bureau figures, 61.1 percent of all Americans were covered by employment-based health insurance coverage in 1995.¹ This unique link between one’s job and one’s medical coverage has continually raised concerns over both the numbers of uninsured and the possible impact of this linkage on labor market outcomes. For example, workers who become unemployed or change jobs often spend a period without health insurance. Among those working full time for the entire 28 month period from 1992 to early 1994, 87 percent were covered for the full period. Among those having one or more job interruption over the period, though, 42 percent went 1 month or more uncovered.² Despite these concerns, any radical reform of the US system which breaks this link is highly unlikely, as the failure of the slightly more modest makeover proposed in the Clinton administration’s 1993 health care reform package illustrates. Instead, smaller changes targeted more directly at the perceived failures of the system are currently underway and are the types of reforms likely to be undertaken in the foreseeable future. The issue, then, is one of gaining a better understanding of what are and are not the effects of the current system. This paper analyzes the impact of employer-provided health insurance on individual job mobility.

Much attention has been paid in recent years to the problem of job-lock, in which workers feel trapped in their current jobs because of fear of losing their current health insurance. While there is no shortage of anecdotal evidence on this issue, serious empirical studies have come to mixed conclusions. At the same time, another potential impact of health insurance on mobility has received much less attention than job-lock, but is the mirror image of that problem. Rather than being locked into a job that, absent the link between employer and health insurance, a worker


²These figures are based on the first seven waves of the 1992 panel of the Survey of Income and Program Participation (SIPP). See Current Population Reports P70-54.
would leave, a worker in need of coverage may be pushed out of a job in which they would otherwise remain. I term this phenomenon “job-push” to parallel the job-lock terminology. This distinction is meaningful, because policy reforms directed at job-lock may have no effect on job-push, or may possibly even worsen the problems.

It is important to recognize that this concept of job-push is separate from the simple notion that jobs offering health insurance are better jobs to which workers always wish to move. Instead, the idea here is that between two jobs with equal compensation value to the firm (i.e. in which the worker is equally productive), having compensation in the form of health coverage may be more valuable to some workers. The presence of job-lock and job-push then imply that worker sorting based on utility will not maximize total product. Instead individuals may stay locked in, or may be pushed in, to jobs with lower productivity than an alternate job not providing health insurance as part of the compensation package.

I investigate these effects of employer-provided health insurance on mobility using a sample of job spells from the Youth panel of the National Longitudinal Survey (NLS-Y). The NLS-Y provides several advantages over some of the data used to investigate job-lock in the past. First, a detailed job history is available that allows me to estimate a proportional hazard model of the probability of exiting a job at any point in the job spell, conditional upon the job having lasted at least that long. This approach allows me to let health insurance coverage, along with other key covariates, to vary over the life of the job spell. Additionally, in later years of the panel, very detailed information on health coverage is available. This information allows me to also estimate probit models using more precise health coverage variables than have typically been used in the past. Finally, the fact that the workers in the NLS-Y are fairly young is valuable in differentiating between job-lock and job-push. In a sample with relatively low mobility rates, it would likely be more difficult to precisely estimate the separate effects.

I find that a substantial portion of what some past studies have estimated as job-lock, may in fact better be categorized as job-push. Weak evidence for this proposition is provided by hazard
model estimates which indicate that the job mobility of a man with employer-provided health insurance is 19 to 35 percent lower in the presence of the pre-existing condition of a pregnant wife. Mobility in the year after the birth of a child, when this pre-existing condition has been lifted, is just 12 to 18 percent higher, though. Thus, one interpretation is that only about half of the higher estimate of the mobility difference is due to job-lock, while the other half is due to job-push.

Somewhat stronger evidence is provided by probit estimates that indicate that the presence of an additional uncovered child increases the mobility of a parent without health insurance by about 15 to 20 percent, while the decrease in mobility implied by an additional child covered by employer provided health insurance is about 14%. At the same time, a standard specification would estimate a significant 28% reduction in mobility and attribute this differential entirely to job-lock.

In the next section, I provide more background on the issue of employer-provided health insurance and mobility and on past studies of job-lock. Section III then describes the data used, while Section IV presents the empirical results. Policy implications are then discussed in Section V, which also concludes.

II. Background

On August 21, 1996, the Health Insurance Portability and Accountability Act of 1996 (H.R. 3103) was signed into law. Among its major provisions are limitations on preexisting condition exclusion periods, along with requirements for the crediting of any periods of previous coverage towards such exclusions.\(^3\) As a result, a worker who is currently fully covered under his employer’s health plan will in general be fully covered under any new employer’s health plan. The law was a direct response to concern over the problem of so-called “job-lock,” which arises from the linkage of health insurance coverage to employer-provided benefit plans, so that maintaining

\(^3\)See H.R. 3103, Sec. 701
one’s current level of health coverage may require remaining “locked” into the current job. An inability to replicate the current level of coverage may occur for many reasons. For example, anecdotal evidence abounds of workers with chronic conditions which will be uncovered on a new job under the pre-existing condition exclusions, or during the qualifying period of many plans. It is just this sort of situation that is affected by the new law.

However, there are other concerns about employer-linked health coverage which remain unaddressed. For example, there remains the possibility that a change in health plans may require a change of physicians, a prospect many workers may find unappealing. Also, it does not appear that the law requires that expenses applied towards one plan’s deductible or out of pocket maximum must be applied towards the new plan’s provisions. As a result, changing jobs may still result in larger out of pocket payments. Additionally, after an uncovered period of greater than 63 days, any previously attained eligibility is forfeited. Finally, the law requires only access to health insurance, not the affordability of such, although there is a provision to perform “a study on the effectiveness of the provisions of this title and the various State laws, in ensuring the availability of reasonably priced health coverage to employers purchasing group coverage and individuals purchasing coverage on a non-group basis” (HR 3103, Sec 191). Conceivably, insurers could respond to HR 3103 with higher premiums, leading ultimately to fewer employer-provided health benefits.

**Empirical Evidence of Effects of Employer-Provided Coverage on Mobility**

While the potential for the linkage of health insurance coverage with employment status to affect the labor market is clear, the empirical evidence on the extent of the effect remains somewhat mixed. Additionally, current studies refer to all differential mobility across groups as evidence of job-lock, making no distinctions between job-lock and job-push. For example, using data on married men from the National Medical Expenditure Survey (NMES), Madrian (1994) finds a significant effect of job-lock, estimating that it is responsible for about a 25 to 40 percent reduction
in mobility among those with employer-provided health insurance. However, using a fairly similar methodology with data from the Panel Study of Income Dynamics (PSID), Holtz-Eakin (1994) concludes that the effect is small and insignificant, both for married men and single workers.

Buchmueller and Valletta (1996) take a different approach, and based on data from the Survey of Income and Program Participation (SIPP) conclude that there is only weak evidence of job-lock among men. However, they find a significant effect for women, implying a reduction in mobility of between 30 and 50 percent. Penrod (1993) also uses the SIPP to conclude that there is limited evidence of job lock.

Cooper and Monheit (1993) take a quite different approach, but use the NMES to reach conclusions similar to Madrian. They calculate, though, that the deadweight loss due to employer-provided health insurance is quite small, totalling between .3 and .4 percent of annual wages (see Monheit and Cooper, 1994). This small deadweight loss results from the fact that only a small fraction of the workforce appears to be subject to job-lock. All of these studies, though, are criticized by Slade (1995), who also argues that government mandates such as the one passed may actually add to the problem by reducing the number of employers offering health coverage. He estimates fixed effect probits using data from the Youth panel of the National Longitudinal Survey (NLS-Y), merged with state-level data on coverage rates and health costs, and based on the positive coefficients on the state-level coverage variable, he concludes that there is no evidence of job-lock. While a specification which mimics that of Madrian does estimate a negative interaction effect, this finding is apparently discounted.

Theoretical Motivation of Empirical Studies

This paper relates most closely to the work of Madrian, Holtz-Eakin, Penrod and Buchmueller and Valletta, although responses to several of the criticisms of Slade are incorporated. To motivate the empirical work theoretically, first consider a simple model of mobility, as specified in Buchmueller and Valletta. They note that it is reasonable to consider the costs of job changing to
be a function of any current fringe benefits which have a nonportable component. In this case, a worker moving between jobs with health insurance plans that are on the surface identical may incur moving costs due to waiting periods, new deductibles, physician changes, etc. as noted above. Such costs may be mitigated, however, to the extent that the worker has alternative coverage (through a spouse, for example), or may be enhanced to the extent that the worker has a preexisting condition, or other above average demand for health care. This discussion implies that the resulting cost function will be of the following form:4

\[
C = \gamma_0 Z + \gamma_1 H + \gamma_2 M + \gamma_3 H^* M + \theta + \epsilon
\]

where,

- \(Z\) is a vector of characteristics affecting moving costs (but not related to health insurance),
- \(H\) is health insurance,
- \(M\) is a vector of characteristics affecting the cost of changing health plans, and
- \(\theta\) reflects individual heterogeneity in turnover propensity.

They further note that the net value of an alternative job can be described as a function of characteristics, \(X\), while that of the current job is a function of the current wage, \(W\), and fringes, along with a match-specific component, \(\mu\). Given, then, that an individual will change jobs if the net value of an alternative job is greater than that of the current job plus turnover costs, an individual will quit if the following holds:5

\[
\alpha X - [\beta_0 W - (\mu + \theta) - (\gamma_0 Z + (\beta_1 + \gamma_1)H + \gamma_2 M + \gamma_3 H^* M)] > (\epsilon_1 + \epsilon_2 - \epsilon_3)
\]

where \(\epsilon_2\) and \(\epsilon_3\) are the error terms for the alternative and current job value equations, respectively.

---

4This is a slight modification of equation (4) in Buchmueller and Valletta.

5This is a slight modification of equation (5) from Buchmueller and Valletta.
**Difference-in-Differences Estimates**

While formal models of this sort can be used to motivate the commonly estimated probit models which include as explanatory variables various individual and job characteristics (X, W, Z), along with health insurance (H), factors affecting the value of health insurance, such as spousal coverage or pre-existing conditions (M) and the interaction (H*H), the distinction between job-lock and job-push is muddied. This distinction is more easily seen by recognizing that one can also interpret the interaction term implied by the simple theoretical model as a regression-based implementation of a “difference-in-differences” estimate of the following form:

\[
\{(\text{mobility of group with employer-provided coverage} - \text{mobility of group without employer-provided coverage})_{\text{group for whom health insurance is more valuable}}\} - \{(\text{mobility of group with employer-provided coverage} - \text{mobility of group without employer-provided coverage})_{\text{group for whom health insurance is less valuable}}\}.
\]

Here the regression to be estimated is of the form \( y = \alpha + \beta_1 \cdot \text{group1} + \beta_2 \cdot x + \beta_3 \cdot \text{group1} \cdot x + \beta_4 Z \), where Z is a vector of other control variables. In this context, then, the dependent variable represents a job transition and group1 is those with employer-provided health insurance (H from above) and x is an indicator of health insurance being more valuable (M from above), meaning \( \beta_3 \) is \( \gamma_3 \) from above.

The implicit assumption of this class of models is that the reduction in mobility due to unobserved job attributes which are correlated with employer-provided coverage will be similar across the two groups and effectively differenced out. Thus, the group for whom health insurance is less valuable is meant to serve as a control for the group for whom coverage is more valuable. The above difference in differences can be rearranged, though, and using some short-hand can then be expressed as follows:

\[
\]
{(more valuable - less valuable)_{employer-provided}} - {(more valuable - less valuable)_{no employer-provided}}

It is now clear that the “control” group is actually quite heterogeneous, including both those with no insurance at all (who may be subject to job-push) and those with coverage from some non job-related source.\textsuperscript{6} It is this last group, with coverage from another source, that might properly serve as a control group for either the group exposed to job-lock (with only employer-provided coverage) and for the group exposed to job-push. The idea here is that this group most closely approximates a world where health coverage is not linked to one’s current job.

Ideally, then we would like to estimate two separate difference in differences:

\{(more valuable - less valuable)_{employer-provided coverage only}\} - \{(more valuable - less valuable)_{nonemployer-provided coverage only}\}, and

\{(more valuable - less valuable)_{no coverage}\} - \{(more valuable - less valuable)_{nonemployer-provided coverage only}\},

where the first measures job-lock and the second measures job-push. If precise measures of health insurance coverage can be obtained, then such estimates can be easily obtained by expanding the coverage indicator to define all four possible groups. If such precise indicators are not available, one still needs to be aware of the problem. Alternatively, one may want to put more stock into the implications of the first difference, rather than the difference-in-differences.\textsuperscript{7} Madrian (1994), does in fact calculate this alternate test of job-lock by looking also at (more valuable - less valuable)_{employer-provided coverage}. In most cases, these estimates imply somewhat smaller effects, as would be expected if job-push is present.

\textsuperscript{6}The treatment group is also heterogeneous, including those with only employer-provided insurance and those with multiple sources of coverage.

\textsuperscript{7}This first difference will be the sum of the interaction term and the value term ($\beta_2 + \beta_3$ in the notation above).
Contributions of Current Study

This study makes several advances on the past work. First, I take several approaches to separate the effect of job-lock from that of job-push. Additionally, rather than looking only a simple snapshot of mobility, I provide some estimates which focus on the entire job spell. Thus, using a proportional hazard model I estimate the probability of exiting a job at any point in the job spell, conditional upon the job having lasted at least that long. As discussed in Buchmueller and Valletta, current job tenure is likely to be an important determinant of mobility, an issue addressed directly by the hazard approach. Similarly, unobserved heterogeneity in individual job-leaving propensities may be important and thus is also incorporated into the analysis. Additionally, Slade (1995) criticizes past studies for ignoring the fact that health insurance coverage status can, and as he shows does, vary over the life of a single job. I allow health insurance coverage, along with all other key covariates, to vary over the life of the job spell to account for this fact.

The transition from a regression framework to a proportional hazard model for a difference-in-differences estimate is quite straightforward. As in Anderson (1992), I assume a proportional hazard of the form

\[ \lambda_i(t) = \lambda_0(t) \exp \{ z_i(t)' \beta \}, \]

where \( \lambda_0(t) \) is the baseline hazard rate at time \( t \), and \( z_i(t) \) is a vector of possibly time-dependent individual characteristics. For the generic difference-in-differences example discussed above, the variables group1, x and group1* x are simply part of the \( z \) vector in this framework, while \( t \) is measured from the start of the job spell.

III. The Data

I use panel data from the NLS-Y are to estimate the effect of employer-provided health
insurance on job mobility. In order to estimate a hazard model, a necessary first step is to transform the data into observations on job spells, rather than individuals. Date of birth, race and sex are obtained from the first interview, while information on date of interview, date of last interview, date of job start and date of job end are extracted from the work history file, along with job characteristics such as the hourly wage, weekly hours worked, industry, occupation and union status. Only data from the first 2 jobs are used, to make the data processing more manageable.

From the dates given, I can determine for each week of the panel what job an individual held, whether an interview took place in that week, if a child was born, or if a marriage started or ended. For each interview year, I also use information on other fringe benefits, job satisfaction, health limitations, educational attainment and the local labor market unemployment rate. Job characteristics are assumed to be constant between interviews, as are most demographic characteristics. I also compute a full marriage and birth history based on the date of birth of up to nine children and the beginning and ending dates of up to three marriages, provided in each survey year. Thus, marital status and number of children vary exactly with the dates given. Additionally, pregnancy is coded as the 3 quarters prior to the birth of a child, while post-pregnancy is coded as the 3 quarters after the birth of a child.

Given this information, each job is then treated as a separate event, and time is rescaled to reflect weeks on the job, which are then condensed into quarters. Finally, jobs for which the ending date was not observed, either due to attrition, due to the end date of the job not being reported as one of the first 2 jobs, or due to the job still being held at the end of the current data collection, are coded as being censored. This sample of job spells is then limited to only those of cross-section sample males who were at least 20 at the start of the job. I also drop jobs in agriculture, construction and the public sector, as well as the self-employed.  

---

8This is similar to Buchmueller and Valletta, who note that the mobility patterns of agricultural workers are atypical, while construction workers typically retain health insurance across jobs through their union. Public sector workers may also have unique arrangements.
remaining industries into Manufacturing, Trade, Services and Other, and occupations into Professional/Managerial, Clerical, Sales/Services and Other. In order to limit the number of time-varying variables to a reasonable number, I assume that the initial industry, occupation and union status of the job remain constant throughout the spell.

Unfortunately, prior to 1989 detailed coverage information is unavailable, forcing me to rely on a simple indicator for presence of employer-provided health insurance, as has been standard. In order to discriminate between job-lock and job-push in the hazard models, I focus mainly on pregnancy as a pre-existing condition, since if individuals are truly locked into a job by this pre-existing condition, then the hazard should increase in the post-pregnancy period. Thus, I use only males in the hazard analysis since the job mobility of a pregnant female is likely to be very different from that of a male with a pregnant wife. Females will be included, however, in some of the later probit analyses where I can make use of more detailed coverage indicators. The final sample for the hazard analysis consists of 5305 job spells. Table 1 presents the sample means and variances.

IV. Empirical Estimates of the Effect of Employer-Provided Health Insurance

A Flexible Baseline Proportional Hazard Model

The first approach taken here is to estimate a proportional hazard model. Formally, the probability of remaining at the same job in the next period, conditional on working there through time t can be expressed as:

\[ P(T_i \geq t + 1 | T_i \geq t) = \exp \left\{ - \exp \left\{ \gamma(t) + z_i(t)' \beta \right\} \right\}, \]

where

\[ \gamma(t) = \ln \left\{ \int_t^{t+1} \lambda_0(u) \, du \right\} \]
is the average baseline hazard over the period. One approach to estimating such a model is to assume a parametric shape for the baseline hazard, such as the Weibull. Generally, though, there is no good \textit{a priori} basis for assuming a specific parameterization of the baseline, and there may be good reason to assume that the baseline is not easily parameterized. Thus, a common alternative is to leave the baseline hazard unspecified and unestimated, as in the Cox partial likelihood approach.\textsuperscript{9} It may be the case, though, that obtaining an estimate of this baseline hazard is desired to examine duration dependence, for instance.

To overcome these drawbacks of the parametric and Cox approaches, I use maximum likelihood techniques to estimate not only the coefficient vector $\beta$, but also the baseline hazard parameters $\gamma(t)$. This approach is discussed in more detail in Meyer (1988, 1990), but briefly, the log-likelihood function for a sample of $N$ job spells will be:

$$L(\gamma, \beta) = \sum_{i=1}^{N} \left[ \delta_i \log \left( 1 - \exp \left( - \exp \left[ \gamma(k_i) + z_i(k_i) \beta \right] \right) \right) - \sum_{t=1}^{k_i-1} \exp \left[ \gamma(t) + z_i(t) \beta \right] \right],$$

where $k_i = \min(\text{int}(T_i), C_i)$, and $\delta_i = 1$ if $T_i < C_i$ and 0 otherwise, with $C_i$ being the censoring time and $T_i$ being the exit time. Note that $\gamma$, $\beta$ and $z_i$ are the hazard parameter, coefficient and covariate vectors as before.

An additional concern when working in the hazard framework is the role of unobserved heterogeneity. Such heterogeneity, if not accounted for, can sometimes lead to spurious findings of duration dependence. For example, imagine that the world is made up of two types of workers - stayers, who have a constant low probability of exit and movers, who have a constant high

\textsuperscript{9}Note that for the case where there are no time-varying covariates, the baseline hazard can be approximated in the Cox approach by calculating exit probabilities at each time with all covariates set to zero.
probability. At any given time, movers are more likely to exit, so that as time goes by the set of individuals at risk of exiting will become more and more heavily represented by stayers. As a result, the estimated hazard rate will be lower as tenure increases. In this case, however, there is no true duration dependence for an individual, since each has a constant probability of exit over time. The method used here is to assume that any unobserved heterogeneity takes a multiplicative form, implying that the proportional hazard model is

\[ \lambda_i(t) = \theta_i \lambda_0(t) \exp \{ z_i(t)' \beta \}, \]

where \( \theta_i \) is a random variable and is assumed to be independent of \( z_i(t) \). Again following Meyer (1988, 1990) and Anderson (1992), a gamma distribution with mean 1 and variance \( \sigma^2 \) is assumed for \( \theta_i \), where it is this variance of the gamma distribution which is to be estimated. The resultant log likelihood is thus a function not only of \( \gamma \) and \( \beta \), but also of \( \sigma^2 \):

\[
L(\gamma, \beta, \sigma^2) = \sum_{i=1}^{N} \log \left\{ 1 + \sigma^2 \cdot \sum_{t=0}^{k_i-1} \exp \{ \gamma(t) + z_i(t)' \beta \} \right\}^{-\sigma^2} - \delta_i \left[ 1 + \sigma^2 \cdot \sum_{t=0}^{k_i} \exp \{ \gamma(t) + z_i(t)' \beta \} \right]^{-\sigma^2}
\]

Standard maximum likelihood techniques can then be used to estimated this model.

**Hazard Model Estimates**

I start by using a very clean indicator of a pre-existing condition, pregnancy. Table 2 presents the results of estimating these models. I begin with a very simple specification, where I control only for basic job and demographic characteristics of the sort available in data sets such as the NMES used by Madrian. There is no control for unobserved heterogeneity. As seen in (1) of Table 2, there is a negative and significant coefficient of -0.415 on the interaction of employer-
provided health insurance and pregnant spouse, meaning that the probability of job exit in any period is lowered by about 34 percent. Note, however, that the pregnancy effect is positive, signalling the possibility of job lock. Thus, the alternative test of job-lock using just the first difference implies only about a 17 percent reduction. In (2), I add additional control variables including provision of other fringe benefits such as life insurance and paid vacation, and job satisfaction. As was the case in Buchmueller and Valletta (1996), the addition of such variables lowers the main effect of health insurance a great deal, from -0.597 to -0.227. The estimated interaction term is essentially unchanged, though, at -0.430. In (3), I allow for the possible presence of unobserved heterogeneity. While the variance of the gamma distribution is significantly different from zero, the estimated coefficients are essentially unchanged.

The addition of unobserved heterogeneity has a large effect on the estimated baseline hazard, however. Figure 1 graphs the estimated baseline both with and without the estimated gamma heterogeneity. As can be clearly seen, the downward trend in the baseline hazard virtually disappears when one accounts for unobserved heterogeneity, implying that the mover-stayer distinction is an important one. While not shown on the graph, it is important to realize that the standard errors around the estimated baseline hazards are increasing over time. In fact, because exits become increasingly rare in the later years of job tenure, jobs lasting more than 8 years are treated as censored at that point. Thus, the baseline hazard is only estimated for 32 quarters, as shown.

As noted the positive effect of pregnancy is consistent with the idea that a man expecting a new baby would like to move to a job which includes health insurance coverage for his expanding family, an idea which seems intuitively plausible. In such a case, the alternative test of job-lock would be clearly preferable, and the pregnancy coefficient could be interpreted as job push. To further differentiate between these two possible effects, I take advantage of the fact that after nine

\footnote{The relatively low hazard in the early quarters is likely a result of having to drop very short jobs that are held only between interview dates when many of the covariates are collected.}
months gestation and the birth of a healthy child, the pre-existing condition has lifted. If an individual had truly been locked into his job by this condition, mobility should now increase. Thus, (4) adds an indicator for a post-birth period, defined as the 3 quarters after the quarter of birth and an interaction with health insurance. This interaction is positive and the point estimate of 0.167 would imply that the probability of ending a job was only about 18 percent higher in this post pregnancy period, compared to the estimated 35 percent drop during pregnancy. While this estimate is not significantly different from zero, it is in line with the more conservative estimate of job-lock. Thus, these results can be interpreted as providing circumstantial evidence that job-push may be an important phenomenon, increasing mobility about as much as job-lock reduces it.

Unlike much of the previous research, though, (1) to (4) are not restricted to married men only, since marital status can vary over the job spell. Thus, the lack of a pre-existing condition could be attributed either to the lack of a pregnant wife, or simply to the lack of any wife. In (5) I move closer to a sample of only married men by restricting the model to only jobs that start with the worker being married. If the worker divorces during the job spell it is not dropped, though. The most notable effect of this restriction is a big drop in the pregnancy interaction term to -0.247, implying just a 22 percent drop. Given the increase in the standard error (to 0.236), the estimate is no longer even marginally significant, though. Interestingly, the main health insurance effect greatly increases, while the main pregnancy effect also falls.

There are several possible interpretations of the differences across (4) and (5). One potential consideration is that many young marrieds are actively planning families. A worker who expects a pregnancy to begin soon may not want to risk losing health coverage just as a pre-existing condition starts. To the extent that many of the non-pregnant marrieds behave as if they might be pregnant, any estimated impact of employer-provided health insurance would be muted.

11 Note that the quarter in which the child is born is coded as neither pregnant nor post-pregnant, so that the post-pregnant period continues for almost a year after the birth.

12 Arguably, these are equivalent situations from the point of view of the possibility of job-lock or job-push.
Similarly, if young married workers without employer-provided health insurance try to move to covered jobs prior to starting a pregnancy, there would be no additional job-push effect of pregnancy. The interaction term could then appropriately be interpreted as job-lock. While the post-pregnancy interaction remains smaller than the pregnancy interaction, implying only a 12 percent rise, the large standard errors make drawing any firm conclusions difficult.

Table 3 estimates additional hazard models using alternate measures of the value of health insurance. In the top panel, number of children is used as the indicator. As argued by Madrian, with more children, the expected health care costs should increase, as will the probability that there is a pre-existing condition in the family. In (1), the full sample is used, while in (2) the sample is again restricted to just those in which the worker was married at the start of the job spell. Starting with (1), the coefficient on the interaction is again negative and significant. The point estimate of -0.159 implies that having one child would reduce mobility by 15 percent for those with employer-provided health insurance, while having two children would reduce their mobility by 37 percent. Again, though, the coefficient on the value term is positive and significant, suggesting the possibility of job-push. In this case, the alternate test of job-lock would actually imply a positive effect on mobility, given the 0.268 coefficient on number of children. Restricting the sample to only those married at the start of the spell cuts the estimated interaction coefficient in half, in this case to -0.080, and the estimate becomes statistically insignificant. The effect of children remains strongly positive, though. Thus, these models are more consistent with job-push affecting larger families than with job-lock.

The second panel focuses more directly on family structure, interacting a marriage dummy with employer-provided health insurance. The estimated effects of both the main effect of marriage and its interaction are very similar to those estimated for the effect of pregnancy in Table 3. Such a result is consistent with the idea that young marrieds may be actively planning families. In order to try to abstract from these issues of family composition, the final panel of Table 3 looks at another alternative indicator that is not related to family structure. Here, a self-report that health
limits the amount or type of work that one can do is taken to denote the presence of a pre-existing condition. With an interaction coefficient of just -0.005, this indicator provides no evidence of an impact of employer-provided health insurance on mobility. Again there is a large positive effect on the value indicator, implying that an alternate test of job-lock would also reject. While this is again suggestive of a role for job-push, this indicator is likely a fairly noisy measure of actual health status.

A final consideration is that the effect of employer-provided health insurance may vary depending on the point in the job spell. Table 4 allows the key interaction coefficient to vary across the first, second, third and fourth or more years on the job. While in no case are the differences across time significant, it may be worth noting that the interaction with a health limit does become more negative over the job spell, as shown in (3). Thus, the very small estimate from Table 3 is the result of small positive estimates early in the spell, and larger negative estimates later in the spell. The other point estimates are generally more stable, although the first year pregnancy effect is somewhat larger than the others.

Probit Model Estimates

While the hazard model results are suggestive of the idea that standard difference-in-differences estimates may overstate job-lock by ignoring the effects of job-push, reliance on single differences may be problematic. Thus, it will be useful to directly obtain difference-in-differences estimates of both job-lock and job-push. Beginning in 1989, more detailed insurance coverage questions began to be asked of the NLS-Y sample members. However, the number of jobs starting after that time is relatively small, at just 583. Thus, I undertake a probit analysis using all job spells in progress in 1989. I then look ahead one year to see if that job is continuing, or has ended. Of the 5305 job spells used in the hazard analysis, 1473 are in progress in 1989. Another

13These models do not include gamma heterogeneity, since convergence could not be obtained on estimates of the variance parameter.
1362 spells of females are also in progress and can be used for some of the analyses. In order to control for tenure in this framework, dummy variables are included for each year of current job tenure. Previously time-varying covariates are defined as of 1989. Rather than the less easily interpreted probit coefficients, the tables present the marginal effects.

I begin by estimating probit models similar to the hazard models estimated above, using just males and pregnancy as a pre-existing condition. The results are shown in Table 5. Models (1) and (2) are of the standard form, where the control group includes both those with no coverage and those with coverage from other sources. As can be seen, these estimates provide strong evidence of job-lock, implying reductions in mobility of over 20 percentage points, or over an 80% reduction compared to the mean exit probability. Unlike the hazard models, the main pregnancy effect is not positive. Thus, the alternate job-lock test is significant, with the sum of the coefficients implying even larger reductions in mobility of near 90 percent.

Models (3) and (4) include separate main effects and interactions for employer-provided coverage only, no coverage and dual coverage. The control group is thus other coverage only. As was hinted at by the insignificant coefficient on pregnancy in the simple models, the coefficient on the employer-provided only interaction is significantly negative and again implies a job-lock effect of over 80 percent. Similarly, the coefficient on the no coverage interaction is insignificant and wrong-signed for job-push. The lack of job-push due to pregnancy in this sample may be related to the fact that this model focuses on only a simple snapshot of mobility around the time of birth.

Table 6 focuses directly on the issue of family size, estimating the effect of additional children on families with children having different types of health coverage. The top panel presents the standard difference-in-differences estimates for males and females, and then males

---

14 Sample sizes given in tables are the actual number of observations used in the estimation and reflect the fact that some observations and variables were dropped that predicted failure perfectly.

15 The interaction of dual coverage and pregnancy was dropped as it predicted exit perfectly.
and females separately. In (1), the interaction term is marginally significant, and at -0.068 implies about an 18% reduction in mobility for an additional child covered by employer-provided health insurance. The main effect of children is positive though, so that the alternate test cannot reject that there is no job-lock. There is an even stronger suggestion of job-push for men, as the coefficient on children in (2) is larger than that on the interaction. This interaction is significant, though, and would imply a 27% change in mobility. For women, no coefficients are even marginally significant.

Turning to the bottom panel, we are hampered by fairly large standard errors, but see some evidence in (5) that for men job-lock was overstated by ignoring job-push in (2). While the point estimate of 0.062 implies about a 19% increase in mobility, the effect is not significant. However, the alternate test of job-push is significant, with a similar-size effect implied of about 20%. By contrast the point estimate of job-lock is half the size of that in (2), implying just a 14% reduction in mobility. For the women, in (6), there is no evidence of job-push, but the point estimate of job-lock is larger than in (3), although still insignificant. Thus, overall, these estimates are consistent with job-push being an important consideration, at least for men with families, but strong conclusions are difficult given the small sample sizes.

Slightly larger samples can be used to estimate models focusing on the effect of additional coverage on mobility. However, it is clear once again that in the presence of job-push the interaction term will overstate job lock. In this case, the difference-in-differences being estimated is (dual coverage - employer-provided coverage only) - (other coverage only - no coverage). Arguably, though, this second difference is itself a measure of job-push, with the first difference then being a better measure of job-lock. Under this interpretation, a negative coefficient on alternate coverage is the sign of job-push, while a positive sum of this coefficient and the interaction is the sign of job-lock. The interaction itself is thus the sum of the job-lock and job-push effects. In looking at Table 7, the significant coefficients are generally found in the top panel, which includes unmarrieds. However, since the point estimates are similar across the two
panels, I will just focus on the larger samples in the top panel. Here, the interaction effect (the difference-in-differences) is always positive, but not significant for men. For women, though, the implied effect is large, at 47 percent. At the same time, the second difference is always negative, but not significant for women. In this case, a 27 percent change in mobility is implied for men and a 17 percent change for men and women combined. At the same time, the first difference is always positive, but never significant at standard levels. For women, this alternate job-lock estimate is marginally significant, though, implying a 33 percent change. Thus, while overall for men and women combined the point estimate on the interaction would imply a 31 to 33 percent effect, about half of this should be attributed to job-push, rather than job-lock.

V. Policy Implications and Conclusions

Properly attributing the difference in job mobility induced by employer-provided health insurance to job-lock or job-push has important policy implications. The recently enacted Health Insurance Portability and Accountability Act of 1996 (H.R. 3103) is explicitly geared toward relieving job-lock, mainly by restricting pre-existing condition exclusions and waiting periods. The goal is for workers to be able to maintain access to health insurance, even when changing jobs. Thus, H.R. 3103 can be expected to remove some of the difference in mobility attributable to job-lock. It should be recalled, though, that there are some aspects of job-lock that remain unaddressed. For example, to the extent a worker is concerned about losing access to a favorite physician, moving to a new health plan may not be optimal. Similarly, while individual access to coverage is guaranteed for those who become unemployed or move to an uncovered job, such coverage may prove to be expensive. Therefore, even with passage of H.R. 3103, some individuals may still feel that they are job-locked.

More importantly, H.R. 3103 cannot be expected to reduce any mobility differential that is due to job-push, since it only guarantees continuing access for previously covered workers.
Thus, workers without employer-provided health insurance will still have an incentive to move to a job that offers such coverage. In fact, with the reduction of exclusions for pre-existing conditions, that incentive may actually be increased. Take the case of a single worker without employer-provided insurance who has a chronic health condition. If this condition would be excluded from coverage at many new jobs offering insurance, this condition does not provide an incentive to move to such a job. Under H.R. 3103, this chronic condition must be covered within 12 months, making such a job all the more attractive. To the extent then that job-push is a significant source of differential mobility, this difference will remain and may even widen.

For the extreme case where there is no job-lock, only job-push, H.R. 3103 could easily do more harm than good. If the mandated changes in waiting periods and restrictions increase the costs of insuring workers, some firms may cease offering coverage all together. In fact, a recent Wall Street Journal article reports that while employer health insurance costs have been falling recently, part of that savings has been achieved by covering fewer workers. If this trend is accelerated by the new legislation, and there is no job-lock to be relieved, then overall welfare would decline. The results of this paper indicate that the truth is likely somewhere in between the extremes of all job-lock and all job-push, with estimates from many samples implying that job-lock and job-push may have approximately equal effects. Estimates of the overall difference in mobility from both sources are similar in magnitude to the range of estimates found in many of the past studies of the impact of employer-provided health insurance on mobility, though, falling mainly in the 20 to 40 percent range.\(^\text{16}\)

Given the similar welfare implications of job-lock and job-push, the estimate by Monheit and Cooper (1994) that the welfare loss due to job-lock is only about 0.3 to 0.4 percent of the wage bill may be a reasonable estimate for the total of both job-lock and job-push. In that case, a gain of less than 0.2 percent of the wage bill attributable to a lowered incidence of job-lock must

\(^{16}\text{With the exception of Holtz-Eakin (1994), who finds no significant effect.}\)
be compared to the costs of H.R. 3103 in order to evaluate the overall effect of the bill. It will be useful then to both track trends in employer-provided coverage and to estimate the impact of that coverage on mobility in the period after H.R. 3103 takes effect. Finally, any future effort to address job-push must keep in mind that the productivity loss is liable to be small - at most 0.2 percent of the wage bill. Thus, costly reforms such as universal coverage or employer mandates could likely only be justified on equity grounds, not efficiency grounds.
References


Table 1
Sample Means and Variances

<table>
<thead>
<tr>
<th>Time Constant Variables</th>
<th>Time Varying Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non White (0.130)</td>
<td>Age (24.197)</td>
</tr>
<tr>
<td></td>
<td>Number of Children (0.724)</td>
</tr>
<tr>
<td>Male (1.000) (0.000)</td>
<td>Hourly Wage (7.180)</td>
</tr>
<tr>
<td></td>
<td>Hours per Week less than 35 (PT) (0.136)</td>
</tr>
<tr>
<td>Manufacturing (0.281) (0.202)</td>
<td>Local UR (7.372)</td>
</tr>
<tr>
<td></td>
<td>Job Has Health Insurance (0.629)</td>
</tr>
<tr>
<td>Trade (0.290) (0.206)</td>
<td>Satisfied at Job (0.419)</td>
</tr>
<tr>
<td></td>
<td>Health Limits Work Can Do (0.033)</td>
</tr>
<tr>
<td>Services (0.294) (0.207)</td>
<td>Wife is Pregnant (0.021)</td>
</tr>
<tr>
<td></td>
<td>Health Insurance* Wife is Pregnant (0.013)</td>
</tr>
<tr>
<td>Professional / Managerial (0.218) (0.171)</td>
<td>Year after Birth (0.075)</td>
</tr>
<tr>
<td></td>
<td>Health Insurance* Year after Birth (0.052)</td>
</tr>
<tr>
<td>Clerical (0.101) (0.091)</td>
<td>Education (12.819)</td>
</tr>
<tr>
<td></td>
<td>Health Insurance* # of Children (0.291)</td>
</tr>
<tr>
<td>Sales / Services (0.305) (0.212)</td>
<td>Married (0.361)</td>
</tr>
<tr>
<td></td>
<td>Health Insurance* Married (0.251)</td>
</tr>
<tr>
<td>Union (0.159) (0.134)</td>
<td>Job Has Life Insurance (0.499)</td>
</tr>
<tr>
<td></td>
<td>Health Insurance* Work Limitation (0.020)</td>
</tr>
<tr>
<td></td>
<td>Job Has Paid Vacation (0.681)</td>
</tr>
<tr>
<td></td>
<td># of Observations (5305)</td>
</tr>
</tbody>
</table>

Notes: Each observation represents a job spell. Sample is based on all cross-section males who were at least 20 at the start of the job spell. Means of time-varying variables are calculated as of the first quarter of job tenure.
Table 2
Hazard Estimates of Probability of Ending Job
Based on Pregnancy as a Pre-Existing Condition

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non White</td>
<td>0.127</td>
<td>0.111</td>
<td>0.232</td>
<td>0.234</td>
<td>0.204</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.052)</td>
<td>(0.076)</td>
<td>(0.076)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.063</td>
<td>-0.068</td>
<td>-0.107</td>
<td>-0.108</td>
<td>-0.134</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Education</td>
<td>-0.008</td>
<td>-0.009</td>
<td>-0.015</td>
<td>-0.016</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Married</td>
<td>-0.041</td>
<td>-0.005</td>
<td>-0.031</td>
<td>-0.030</td>
<td>-0.072</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.046)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.534)</td>
</tr>
<tr>
<td>Number of Children</td>
<td>0.110</td>
<td>0.117</td>
<td>0.152</td>
<td>0.156</td>
<td>0.148</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.024)</td>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Health Limits Work</td>
<td>0.358</td>
<td>0.371</td>
<td>0.507</td>
<td>0.508</td>
<td>0.400</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.102)</td>
<td>(0.139)</td>
<td>(0.140)</td>
<td>(0.224)</td>
</tr>
<tr>
<td>Hours per Week &lt; 35 (PT)</td>
<td>0.254</td>
<td>0.115</td>
<td>0.100</td>
<td>0.100</td>
<td>0.365</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.056)</td>
<td>(0.074)</td>
<td>(0.074)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>Union</td>
<td>-0.277</td>
<td>-0.232</td>
<td>-0.366</td>
<td>-0.368</td>
<td>-0.495</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.055)</td>
<td>(0.075)</td>
<td>(0.076)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Hourly Wage</td>
<td>-0.026</td>
<td>-0.021</td>
<td>-0.028</td>
<td>-0.028</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Local UR</td>
<td>--</td>
<td>-0.019</td>
<td>-0.023</td>
<td>-0.023</td>
<td>-0.053</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.006)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Satisfied at Job</td>
<td>--</td>
<td>-0.272</td>
<td>-0.297</td>
<td>-0.298</td>
<td>-0.280</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.042)</td>
<td>(0.056)</td>
<td>(0.056)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Job has Life Insurance</td>
<td>--</td>
<td>-0.306</td>
<td>-0.373</td>
<td>-0.374</td>
<td>-0.442</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.058)</td>
<td>(0.079)</td>
<td>(0.079)</td>
<td>(0.125)</td>
</tr>
<tr>
<td>Job has Paid Vacation</td>
<td>--</td>
<td>-0.389</td>
<td>-0.611</td>
<td>-0.615</td>
<td>-0.617</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.055)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.125)</td>
</tr>
<tr>
<td>Job has Health Insurance</td>
<td>-0.597</td>
<td>-0.227</td>
<td>-0.299</td>
<td>-0.304</td>
<td>-0.491</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.063)</td>
<td>(0.086)</td>
<td>(0.087)</td>
<td>(0.138)</td>
</tr>
<tr>
<td>Wife is Pregnant</td>
<td>0.228</td>
<td>0.238</td>
<td>0.216</td>
<td>0.217</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.125)</td>
<td>(0.142)</td>
<td>(0.142)</td>
<td>(0.185)</td>
</tr>
<tr>
<td>Health Insurance*Pregnant</td>
<td>-0.415</td>
<td>-0.430</td>
<td>-0.430</td>
<td>-0.431</td>
<td>-0.247</td>
</tr>
<tr>
<td></td>
<td>(0.164)</td>
<td>(0.164)</td>
<td>(0.182)</td>
<td>(0.182)</td>
<td>(0.236)</td>
</tr>
<tr>
<td>Year After Birth</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.165</td>
<td>-0.154</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.215)</td>
<td>(0.244)</td>
</tr>
<tr>
<td>Health Insurance*After Birth</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.167</td>
<td>0.112</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.296)</td>
<td>(0.352)</td>
</tr>
<tr>
<td>Estimated Variance of Gamma</td>
<td>--</td>
<td>--</td>
<td>0.940</td>
<td>0.955</td>
<td>0.497</td>
</tr>
<tr>
<td>Heterogeneity Distribution</td>
<td></td>
<td></td>
<td></td>
<td>(0.148)</td>
<td>(0.150)</td>
</tr>
</tbody>
</table>

-log likelihood         -10263.15 -10188.22 -10163.52 -10163.24 -3416.816

Notes: Models (1) to (4) are estimated using 5305 job spells from all cross-section males who were at least 20 at the start of the job spell. Model (5) is restricted to the 1914 job spells in which start with the worker being married. All models also include 3 industry class variables and 3 occupation class variables. All variables shown except for NonWhite and Union are time-varying. Standard errors in parentheses.
Table 3
Hazard Estimates of Probability of Ending Job
Based on Alternate Indicators of Value of Health Insurance

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Job has Health Insurance</strong></td>
<td>-0.231</td>
<td>-0.408</td>
</tr>
<tr>
<td></td>
<td>(0.092)</td>
<td>(0.163)</td>
</tr>
<tr>
<td><strong>Number of Children</strong></td>
<td>0.268</td>
<td>0.203</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.068)</td>
</tr>
<tr>
<td><strong>Health Insurance*Number of Children</strong></td>
<td>-0.159</td>
<td>-0.080</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.080)</td>
</tr>
<tr>
<td><strong>Estimated Variance of Gamma</strong></td>
<td>0.945</td>
<td>0.476</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td>(0.189)</td>
</tr>
<tr>
<td><strong>-log likelihood</strong></td>
<td>-10043.785</td>
<td>-3416.828</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Job has Health Insurance</strong></td>
<td>-0.152</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td></td>
</tr>
<tr>
<td><strong>Married</strong></td>
<td>0.261</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td></td>
</tr>
<tr>
<td><strong>Health Insurance*Married</strong></td>
<td>-0.444</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td></td>
</tr>
<tr>
<td><strong>Estimated Variance of Gamma</strong></td>
<td>0.925</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.147)</td>
<td></td>
</tr>
<tr>
<td><strong>-log likelihood</strong></td>
<td>-10157.150</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Job has Health Insurance</strong></td>
<td>-0.323</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td></td>
</tr>
<tr>
<td><strong>Health Limits Work</strong></td>
<td>0.513</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.211)</td>
<td></td>
</tr>
<tr>
<td><strong>Health Insurance*Health Limit</strong></td>
<td>-0.005</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.281)</td>
<td></td>
</tr>
<tr>
<td><strong>Estimated Variance of Gamma</strong></td>
<td>0.956</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td></td>
</tr>
<tr>
<td><strong>-log likelihood</strong></td>
<td>-10166.078</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Model (1) is estimated using 5305 job spells from all cross-section males who were at least 20 at the start of the job spell. Model (2) is restricted to the 1914 job spells in which start with the worker being married. All models include controls for industry class, occupation class, race, age, education, married, number of children, health limitations, part-time, union member, hourly wage local UR, job satisfaction, life insurance, paid vacation, pregnant wife and recent birth of a child. Standard errors in parentheses.
<table>
<thead>
<tr>
<th>Value of Current Health Insurance Indicator Is:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wife is Pregnant</td>
<td>0.238</td>
<td>0.199</td>
<td>0.391</td>
<td>0.229</td>
</tr>
<tr>
<td>Job has Health Insurance</td>
<td>-0.227</td>
<td>-0.181</td>
<td>-0.248</td>
<td>-0.108</td>
</tr>
<tr>
<td>First Year on Job</td>
<td>-0.706</td>
<td>-0.099</td>
<td>0.017</td>
<td>-0.452</td>
</tr>
<tr>
<td>Second Year on Job</td>
<td>-0.212</td>
<td>-0.113</td>
<td>0.160</td>
<td>-0.331</td>
</tr>
<tr>
<td>Third Year on Job</td>
<td>-0.582</td>
<td>-0.191</td>
<td>-0.217</td>
<td>-0.405</td>
</tr>
<tr>
<td>Fourth or More Year on Job</td>
<td>-0.432</td>
<td>-0.121</td>
<td>-0.414</td>
<td>-0.312</td>
</tr>
</tbody>
</table>

| - log likelihood                               | -10186.377 | -10186.186 | -10190.462 | -10179.923 |

Notes: All models are estimated using 5305 job spells from all cross-section males who were at least 20 at the start of the job spell. All models include controls for industry class, occupation class, race, age, education, married, number of children, health limitations, part-time, union member, hourly wage local UR, job satisfaction, life insurance, paid vacation, pregnant wife and recent birth of a child. Standard errors in parentheses.
Table 5
Based on Pregnancy as a Pre-Existing Condition

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wife is Pregnant</td>
<td>-0.027</td>
<td>-0.015</td>
<td>0.019</td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.048)</td>
<td>(0.063)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>Wife has Coverage from</td>
<td>-0.037</td>
<td>-0.032</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Husband’s Job</td>
<td>(0.043)</td>
<td>(0.040)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wife has Coverage from</td>
<td>-0.243</td>
<td>-0.225</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Husband’s Job*Wife is Pregnant</td>
<td>(0.093)</td>
<td>(0.087)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wife has Coverage only from</td>
<td>--</td>
<td>--</td>
<td>0.005</td>
<td>-0.007</td>
</tr>
<tr>
<td>Husband’s Job</td>
<td></td>
<td></td>
<td>(0.052)</td>
<td>(0.050)</td>
</tr>
<tr>
<td>Wife has Coverage only from</td>
<td>--</td>
<td>--</td>
<td>-0.245</td>
<td>-0.225</td>
</tr>
<tr>
<td>Husband’s Job*Wife is Pregnant</td>
<td></td>
<td></td>
<td>(0.100)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Wife has No Coverage</td>
<td>--</td>
<td>--</td>
<td>0.084</td>
<td>0.070</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.041)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Wife has No Coverage*Wife is</td>
<td>--</td>
<td>--</td>
<td>-0.062</td>
<td>-0.064</td>
</tr>
<tr>
<td>is Pregnant</td>
<td></td>
<td></td>
<td>(0.085)</td>
<td>(0.099)</td>
</tr>
<tr>
<td>Wife has Dual Coverage</td>
<td>--</td>
<td>--</td>
<td>0.025</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.083)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Married Only</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>P-value for alternate job-lock test</td>
<td>0.004</td>
<td>0.005</td>
<td>0.012</td>
<td>0.016</td>
</tr>
<tr>
<td>P-value for alternate job-push test</td>
<td>--</td>
<td>--</td>
<td>0.471</td>
<td>0.573</td>
</tr>
<tr>
<td>Dependent Mean</td>
<td>0.297</td>
<td>0.268</td>
<td>0.300</td>
<td>0.272</td>
</tr>
<tr>
<td>Pseudo-R-squared</td>
<td>0.1436</td>
<td>0.1523</td>
<td>0.1422</td>
<td>0.1489</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1473</td>
<td>814</td>
<td>1461</td>
<td>802</td>
</tr>
</tbody>
</table>

Notes: Models (1) and (3) are estimated using job spells from all cross-section males who were at least 20 at the start of the job spell and for whom the spell was ongoing in 1989. Models (2) and (4) are restricted to those married in 1989. All models include controls for year of tenure, industry class, occupation class, race, age, education, number of children, health limitations, part-time, union member, hourly wage, local UR, job satisfaction, life insurance, and paid vacation. Models (1) and (3) include a control for married. Marginal effects calculated from probit coefficients are shown. Standard errors in parentheses. Marginal effects calculated from probit coefficients are shown. Standard errors in parentheses. Models (3) and (4) drop 12 observations where the wife is pregnant and holds dual coverage.
Table 6
Based on Number of Children
as an Indicator of the Value of Health Insurance

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Kids</td>
<td>0.036</td>
<td>0.053</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.027)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Kids have Coverage from Parent’s Job</td>
<td>0.025</td>
<td>0.137</td>
<td>-0.085</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.094)</td>
<td>(0.121)</td>
</tr>
<tr>
<td>Kids have Coverage from Parent’s Job*Number of Kids</td>
<td>-0.068</td>
<td>-0.087</td>
<td>-0.061</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.045)</td>
<td>(0.070)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sample</th>
<th>Males &amp; Females</th>
<th>Males Only</th>
<th>Females Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Observations</td>
<td>1292</td>
<td>623</td>
<td>652</td>
</tr>
</tbody>
</table>

|                        | (1)         | (2)         | (3)         |
| Number of Kids         | 0.031       | 0.005       | 0.052       |
|                        | (0.030)     | (0.053)     | (0.039)     |
| Kids have Coverage only from Parent’s Job | 0.038       | 0.052       | -0.003      |
|                        | (0.089)     | (0.128)     | (0.147)     |
| Kids have Coverage only from Parent’s Job*Number of Kids | -0.066       | -0.045       | -0.092      |
|                        | (0.045)     | (0.064)     | (0.082)     |
| Kids have No Coverage  | 0.001       | -0.133      | 0.162       |
|                        | (0.078)     | (0.120)     | (0.112)     |
| Kids have No Coverage*Number of Kids | 0.009       | 0.062       | -0.056      |
|                        | (0.037)     | (0.060)     | (0.053)     |
| Kids have Dual Coverage | -0.095      | -0.226      | -0.019      |
|                        | (0.195)     | (0.281)     | (0.253)     |
| Kids have Dual Coverage*Number of Kids | -0.020      | 0.109       | -0.086      |
|                        | (0.112)     | (0.192)     | (0.142)     |

<table>
<thead>
<tr>
<th>Sample</th>
<th>Males &amp; Females</th>
<th>Males Only</th>
<th>Females Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Observations</td>
<td>1292</td>
<td>623</td>
<td>652</td>
</tr>
</tbody>
</table>

Notes: Models are estimated using job spells from all cross-section individuals with children who were at least 20 at the start of the job spell and for whom the spell was ongoing in 1989. All models include controls for year of tenure, industry class, occupation class, race, age, education, married, health limitations, part-time, union member, hourly wage, local UR, job satisfaction, life insurance, and paid vacation. Marginal effects calculated from probit coefficients are shown. Standard errors in parentheses. See text for description of samples and alternate tests.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has Coverage from Job</td>
<td>-0.240</td>
<td>-0.208</td>
<td>-0.293</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.037)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Has Alternate Coverage</td>
<td>-0.054</td>
<td>-0.082</td>
<td>-0.047</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.039)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Has Coverage From Job*</td>
<td>0.105</td>
<td>0.088</td>
<td>0.160</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.089)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>Married Only Sample</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>Males &amp; Females</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>P-value for alternate job-lock test</td>
<td>0.357</td>
<td>0.956</td>
<td>0.105</td>
</tr>
<tr>
<td>Dependent Mean</td>
<td>0.284</td>
<td>0.297</td>
<td>0.344</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.156</td>
<td>0.151</td>
<td>0.157</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>2835</td>
<td>1473</td>
<td>1327</td>
</tr>
<tr>
<td></td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>Has Coverage from Job</td>
<td>-0.215</td>
<td>-0.124</td>
<td>-0.311</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.052)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Has Alternate Coverage</td>
<td>-0.048</td>
<td>-0.078</td>
<td>-0.055</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.051)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Has Coverage From Job*</td>
<td>0.095</td>
<td>0.082</td>
<td>0.165</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.099)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>Married Only Sample</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Males &amp; Females</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>P-value for alternate job-lock test</td>
<td>0.404</td>
<td>0.929</td>
<td>0.139</td>
</tr>
<tr>
<td>Dependent Mean</td>
<td>0.309</td>
<td>0.268</td>
<td>0.354</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.150</td>
<td>0.141</td>
<td>0.156</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1728</td>
<td>814</td>
<td>892</td>
</tr>
</tbody>
</table>

Notes: Models are estimated using job spells from all cross-section individuals who were at least 20 at the start of the job spell and for whom the spell was ongoing in 1989. All models include controls for year of tenure, industry class, occupation class, race, age, education, married, health limitations, part-time, union member, hourly wage, local UR, job satisfaction, life insurance, and paid vacation. Marginal effects calculated from probit coefficients are shown. Standard errors in parentheses. See text for description of samples and alternate tests.