EMPIRICAL ANALYSES OF JOB DISPLACEMENTS AND PRODUCTIVITY

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Melissa Jo Bjelland

January 2007

EMPIRICAL ANALYSES OF JOB DISPLACEMENTS AND PRODUCTIVITY

Melissa Jo Bjelland, Ph.D.

Cornell University 2007

The first chapter of this dissertation integrates the existing literatures on displacement and health by examining the enduring effects of job dislocations that are induced by employment shocks. A joint estimation of hourly wage rates and weekly hours illuminates the disparities in these economic outcomes that exist between those who have reestablished themselves in the workplace subsequent to a layoff and those who have returned to work following the onset of a disability relative to those with uninterrupted job histories. As an extension of these ideas, employment transitions and workplace adjustments are modeled to capture spousal reactions to these shocks. Multiple indicators of health from the Survey of Income and Program Participation and Social Security Administrative benefits records are incorporated into the analyses of those with impairments that prompted job loss. These measures allow knowledge to be gleaned regarding the qualitative differences in the lasting impacts of job cessation resulting from medically diagnosed illnesses as compared to estimates uncovered using survey data sources alone. By considering time durations following these periods of separation in light of these indicators of well-being, a more comprehensive understanding of the long-run repercussions of employee-employer separation is acquired.

The second and third chapters, representing joint work with John M. Abowd and Kevin L. McKinney, address the research and data preparation that are part

of a larger Bureau of Labor Statistics and Bureau of the Census project. We examine the manner in which changes in the composition of the labor force impact productivity by exploiting measures of human capital, or skill. The BLS has previously employed a multifactor productivity model based upon a Jorgensonian price of labor to explore changes in the index of labor composition within industry division and year by gender. We choose instead to utilize a Beckerian price of labor that incorporates skill to examine this index. For this purpose, human capital is derived from the estimation of a wage equation that includes both person and firm fixed effects. This technique enables us to characterize how differences in labor force composition affect labor quality within and between industry divisions over time.

BIOGRAPHICAL SKETCH

Melissa Bjelland was born and raised in Tucson, Arizona, where she graduated from University High School in 1994. She earned her B.S. in Mathematics from the University of Arizona in 1998, her M.S. in Economics from Cornell University in January 2004, and expects to receive her Ph.D. in Economics from Cornell in January 2007. The last four years of her graduate studies were spent in the Washington, D.C. area where she worked to complete her dissertation using confidential data at the U.S. Bureau of the Census while under the employ of the Bureau of Labor Statistics.

For Dr. Thomas R. Elliott, M.D., who inspired the first chapter of this dissertation.

ACKNOWLEDGEMENTS

I would like to express my gratitude to the members of my thesis committee: John Abowd, George Jakubson and Kosali Simon. I particularly appreciate the guidance that George and Kosali provided during my last year while I was preparing for and engaged in the formal job market for Economists. As for John, I genuinely have enjoyed working with you on a variety of projects under development at the Longitudinal Household-Dynamics Program. In setting high, attainable standards, you have made me challenge myself in ways I never imagined I would be when I first set foot on Cornell's campus. I am grateful that you consistently make yourself readily available via e-mail, phone, or video, and that you manage to stay so well in tune with those with whom you work. Thank you for believing in, encouraging, and mentoring me. I feel extremely blessed to have had the opportunity to work with such a creative group of highly-capable people under your watch.

I am indebted to my colleagues at the Longitudinal Employer-Household Dynamics Program for teaching me both indirectly and directly a great deal about the tools involved in Economic research. From Lars, I learned how to program in both Stata and SAS using the most sophisticated methods and discovered Unix scripting. Martha was my guide when it came to working with the Survey of Income and Program Participation; her willingness to share her knowledge and years of data work made my dissertation possible. Gary and Simon made my life much easier by devoting themselves to the creation of a set of Sequential Regression Multiple Imputation programs that I utilized to build the base files for my second chapter. Kevin, my human capital buddy, is someone whom I sincerely admire for his thoroughness and quality work. As for Bryce, Erika, and Kristin, it has been an absolute pleasure to work with you.

I am eternally grateful for the love, support, and kindness of my family and friends throughout this process. To my mom, who has always been by my side, you continue to inspire me and give me strength. To my father, who always encouraged me to be my best, thank you for reminding me that it is important for me to take time to enjoy my life while pursuing my dreams. To Mames, or Amy as the world knows her, I thank you for being not only my big sister, but also for being one of my favorite people. And to Yuliya, Karen, and Geeta, who through a variety of situations have found the courage to press forward into tomorrow, I am so happy to have you in my life.

Most of all, I thank Aaron, who with his unconditional love, understanding, and sage wisdom always makes my spirit soar. I cannot imagine having gone through these past few years without you by my side. The calm patience of your gentle soul brings me such peace and joy. I am honored to have you as my best friend and husband.

And finally, I thank the Bureau of Labor Statistics for funding the project that brought me to the Longitudinal Employer-Household Dynamics Program at the U.S. Bureau of the Census and enabled me to work with such a wonderful collection of individuals during the last years of my graduate studies.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Are the Lasting Effects of Employee-Employer Separations induced by Layoff and Disability Similar? Exploring Job Displacements using Survey and Administrative Data

1.1 Introduction

Studies that explore the lingering impacts of mass layoff have extensively documented the persistence of firm-side shocks that result in permanent job loss. As an inaugural researcher in this area, Ruhm (1991) noted the insufficient knowledge of the adjustment period subsequent to employer-initiated displacing events and endeavored to address this issue. His discovery of substantial earnings losses that are sustained for years beyond the date of dislocation propagated a proliferation of papers, each with intriguing insights about the duration and magnitude of the lasting scars of job separations.[1]However, the development of these concepts has remained narrowly focused on layoffs and consistently has excluded any consideration of the lasting effects of analogous shocks to individual workers, such as onsets of serious illness or disability, that cause employer-employee matches to conclude.

My study corrects for this oversight by comparing the enduring detrimental

[1]These papers include articles authored by Jacobson, LaLonde, and Sullivan (1993); Stevens (1997); Fairlie and Kletzer (1998); and Kletzer (1998). Fallick (1996) surveys advancements in this literature.

impacts of past firm and individual shocks and, in doing so, presents a unique opportunity to unify the ideas found within the literatures on displacement and health. By linking economic outcomes to latent impairments that initiated past job dislocations, this paper supplements the more traditional health studies that have generally aimed to explore the role of contemporaneous well-being on labor force decisions.[2] Evidence of workers scarred by an unanticipated layoff is abundant, but the severity is unparalleled to the repercussions experienced by those who have parted from their employer as the result of a disabling condition. This is because those returning to work following a displacing health shock may be economically disadvantaged not only by the abrupt job termination, but also by the compounding factors relating to any health problems that persist subsequent to their reemployment.

Within the context of the family, the implications of job loss are not limited to the affected worker alone. Individuals within a household exhibit compensating labor force behaviors in the aftermath of another member's unemployment or illness.[3] Results are not consistent across these studies, however. I additionally investigate spousal reactions to dislocations in order to determine the manner in which layoff and poor health influence married couples as a unit. The differential behaviors of workers and their nondisplaced spouses who are impacted by these two types of events provide an improved understanding of the strengths of shocks to the demand and supply of workers.

For this purpose, I consider the lasting effects of job separations using multiple

[2]See Currie and Madrian (1999) for a review of health papers of this sort that utilize data from developed countries. Thomas (2001) provides an excellent survey of studies of this nature that utilize clinical indicators of health status.

[3]See Charles (1999), Coile (2004), Parsons (1977), and Stephens (2001) for relevant papers on the added worker effect.

panels of the Survey of Income and Program Participation (SIPP) and integrated benefits records from the Social Security Administration (SSA). The SIPP has the advantage of providing longitudinal information on demographic and job characteristics, including reasons for work cessation, without restricting the sample to those who are more advanced in age, as is the case with the Health and Retirement Study. The populations examined include individuals whose positions are eliminated as part of layoffs and those who are induced to leave their places of employment as the result of work-limiting conditions.[4] A subset of the employed who are highly attached to the labor force is additionally analyzed using evidence of workplace exits from the records of Social Security Disability Insurance (SSDI) applicants. Since it is plausible that a worker may experience an episode of ill health that shocks her out of work but is not severe enough to meet the impressive standards of SSA for acceptance into either program, the purpose of the inclusion of administrative indicators of health exits is not to strictly assess the validity of the survey measures. Instead, they are presented to provide an understanding the qualitative differences in the lasting effects of acute traumas that have been medically diagnosed as distinguished from the results uncovered using survey data sources alone.

I first review motivating papers to provide background knowledge of the studies that contributed to the development of this topic. Discussed are articles in which

[4]Work-limiting conditions in this study refer to ill health, disability, and other medical impairments that prevent or restrict an individual from participating in activities that are required for gainful employment. Temporary ailments are not considered to be severe enough to sufficiently impede an individual's abilities for any great duration and are thus not counted among these afflictions. Within the context of this study, people with work-limiting conditions will be referred to as being of ill health, disabled, or impaired despite an awareness of the conceptual differences implied by these terms.

health status and spells out of the work force are individually linked to labor behaviors in order to outline the parallels between these bodies of work. I then present a model to explore the convergence of these pieces. I do this by examining the lasting impacts that displacements resulting from layoff and ill health have upon wages and hours in the years following the events by using definitions of wellness from multiple sources. These ideas are then extended within the context of the dynamics of a married couple to determine how spousal job loss influences the economic outcomes, including the duration of employee-employer matches, of nondisplaced partners.

My research reveals that behaviors during the ensuing adjustment period vary by the reason for the unanticipated exit, the number of years that have passed since the event occurred, and the demographic characteristics of the worker that include gender, race, and education. While individuals with a layoff or disability in their past appear to be economically burdened by displacements, those who were unexpectedly forced to part with their employers because of layoff experience rapid improvements to their hourly wage rates while spending more time in the office than do their nondisplaced counterparts. Those with debilitating health shocks that induced a job separation have reemployment wages and hours that are simultaneously and negatively impacted, which results in financial losses that endure far longer. I find that estimates from the administrative measures of health mirror the qualities of those that utilize self-reports of functional limitations, although the magnitude of the impact is more detrimental for those who have applied for SSDI benefits. This result is most exacerbated in the spousal analyses, as women with husbands who have applied for administrative benefits appear to be transitioning to new positions that provide less pay and allow them to sharply reduce their workweeks.

1.2 Motivating Studies

Among the articles that have attempted to address the realization of past conditions in current labor market outcomes is a piece authored by Chirikos and Nestel (1985). Using the National Longitudinal Surveys of Older Men in 1976 and Mature Women in 1977, Chirikos and Nestel construct four variables from a retrospective history of self-reported health status: continuously good, improving, deteriorating, and continuously poor health over the previous ten years.[5] To study the relationship between well-being and income, they estimate a two-equation model for four sex-race groups. A fascinating result of their procedure is that a history of poor health, whether continual or changing, reduces current economic welfare. This is true for both individuals who have household resources available to them and for those who exhibit increased efforts to devote more time to current employment. It is possible that Chirikos and Nestel unknowingly were reporting on the lasting impacts that periods of forced job withdrawal- rather than strictly ill health- have upon labor outcomes in the long run.

An interesting piece that stratifies those suffering from ailments in order to emphasize the import of disease severity in deriving results is by Smith (1999). Longitudinal survey data from the Health and Retirement Survey (HRS) and Asset and Health Dynamics of the Oldest Old survey (AHEAD) enable him to consider the manner in which unanticipated changes in well-being impact an individual. Without allowing for his estimates to be contaminated by those who are impaired

[5] In categorizing people as having one of four types of health histories, Chirikos and Nestel use self-reported impairments, a rating of perceived health, and the existence of conditions that include those which prohibit employment.

to a differing degree, Smith is able to deduce that severe health shocks produce a 15% decrease in the probability of continued employment, a reduction in own earnings of $2,639, and cause impaired individuals to work four fewer hours per week in the subsequent period. For minor shocks, Smith finds a 5% decrease in the probability of remaining in the work force, a $1,638 decline in job income, and a reduction of time at work by just over one hour following the event.[6] The probability of staying at work falls by only 6% after a period of at least three years, and so Smith additionally finds that the effects of a major health problem endure, but do diminish with time.

Identifying those with more detrimental conditions is clearly key in ensuring that results are not clouded by mixture with the population of individuals with transient ailments. In reviewing breast cancer survivors, Bradley, Bednarke, and Neumark (2001) are able to focus their attention on whether and how substantial health shocks continue to impact a woman's labor market outcomes following recovery. Wave 1 of the HRS provides information on the amount of time that has elapsed since a diagnosis of breast cancer. A probit model reveals that women with histories of this disease are 9% less likely to be working than those without. Conditional on employment, women who have survived three or more years since their diagnosis work approximately 4 more hours and earn 23% more than the noncancer control group; those who have survived two years or fewer do not work a different number of hours nor do they earn more. Without utilizing information about whether the women diagnosed with breast cancer parted with their places of employment or were on leave, it is difficult to surmise whether the estimates of Bradley, Bednarke, and Neumark represent outcomes stemming from actual

[6]The findings mentioned in this review are from the HRS sample and are for impairments that occurred in the previous two years.

employee-employer separations.

Research has documented that layoffs result in lasting effects on economic prosperity, but such work has as of yet not been applied to the framework of forced medical exits from the labor market. Ruhm (1991) considers whether workers in the former context suffer from persistent negative effects related to job displacements which leave them scarred. He explains that "dislocated individuals are defined as scarred if they continue to earn less or to be unemployed more than their nondisplaced counterparts, even after the conclusion of a several-year adjustment period." Using data from heads of households from the Panel Study of Income Dynamics for the 1969-1982 waves, Ruhm partitions the years of the survey to examine histories of employment around five base years. He desires to draw conclusions for those permanently displaced in mass layoffs or plant closures, and does so by estimating three sets of OLS wage regressions and tobit unemployment models in an attempt to control for unobserved heterogeneity. Ruhm's results reveal that while current unemployment has a minimal impact on future joblessness, wage effects from separation are large in magnitude and persist through time. In the year following separation, weekly earnings of displaced workers are 16% lower than those of the nondisplaced, and they remain 14% lower four years later.

Ruhm's work is extended by Jacobson, LaLonde, and Sullivan (1993) using a 5% sample of longitudinally integrated employer-employee administrative data from the state of Pennsylvania for the years 1974-1986. These data enable the authors to separately analyze the within and between effects of displacement on high-tenure individuals. They find that those terminated from positions in distressed firms experience lasting earnings losses that average 25% per year. The authors also determine that these losses are not highly dependent upon worker gender and age, they are significant even for those who are able to obtain subsequent work in firms with similar characteristics, and they arise even prior to the point of separation. Similar findings are uncovered by multiple sources, indicating that they are nationally representative and not just particular to a singular state. [7]

The scope of my research is not limited to the earnings losses of those who have personally suffered layoff or disability. Much remains to be learned about the manner in which these different events affect a spouse, particularly because available papers on these topics present results that appear to be highly dependant upon the implemented methods and data.

Within the context of a married couple, a study by Parsons (1977) finds using the Productive Americans Survey that the responses of spouses of infirm individuals vary by gender: men work fewer hours, whereas women work more following the realization of this type of shock. Haurin (1989) discovers small and statistically insignificant responses of women to the changing health quality of their husbands. Severe impairments, however, are found to notably affect spouses. Consistent with this, Coile (2004) uses the HRS to explore the added worker effect and finds that when husbands suffer a severe health trauma, women decrease labor supply. This is clear evidence of wives choosing to substitute time in the home for hours spent at work when their spouses are recovering. Charles (1999) also employs the HRS and determines, contrary to Coile, that women work more while men reduce labor supply subsequent to the disability of a spouse. Similar behaviors are apparent in a paper by Stephens (2001), who focuses instead on wives' labor supply reactions to husbands' layoffs. He finds that women are able to replace 25% of their husbands' lost income by becoming more present in the work force over the course of several

[7] Fallick (1996) provides a review.

years.

Despite noted advancements in studies that incorporate measures of health and that explore displacing events, the apparent isolation of research in these areas has resulted in a nebulous concept of the manner in which previous disability-related dislocations might affect workers and their spouses. This paper shifts the focus of both bodies of literature in order to appropriately address the differential lasting impacts of forced separations that are caused by firm and individual shocks. The plights of the reemployed can clearly be examined within a structured framework that permits such a comparison.

1.3 Model

1.3.1 Own Job Displacements

The lasting economic consequences of layoffs and disability-related job dislocations of individual i employed at job j in time t are determined by jointly estimating a regression of the logarithm of the real hourly wage rate, W_{ijt}, and the logarithm of weekly hours, R_{ijt}, conditional on employment as defined by

$$
\begin{aligned}
W_{ijt} \quad &= \quad X_i'\beta_{W1} + X_{ij}'\beta_{W2} + X_{it}'\beta_{W3} + \\
&\quad \sum_{m=1}\gamma_{WL_m}L_{it}^m + \sum_{m=1}\gamma_{WH_m}H_{it}^m + \theta_i + \varphi_{ij} + \varepsilon_{ijt}, \qquad (1.1)\\
R_{ijt} \quad &= \quad W_{ijt}\delta + X_i'\beta_{R1} + X_{ij}'\beta_{R2} + X_{it}'\beta_{R3} + \\
&\quad \sum_{m=1}\gamma_{RL_m}L_{it}^m + \sum_{m=1}\gamma_{RH_m}H_{it}^m + \alpha_i + \chi_{ij} + \eta_{ijt}. \qquad (1.2)
\end{aligned}
$$

These equations are comprised of a vector, X_i, of time-invariant observable characteristics of the worker that include race, gender, education groups, and ethnicity. Static employee-employer match characteristics, X_{ij}, are union status, industry division, and type of employment. Time-varying worker characteristics, X_{it}, consist of marital status, number of children in the household, gender interacted with martial status and number of children in the household, census regional division of residence, and a piecewise-linear spline of changing work force experience. Controls for SIPP panel year are additionally incorporated into the model.[8]

Within this system, I estimate the persistent losses associated with employer-employee displacements in order to measure the quantities that the two populations of interest work and earn as compared to those with continuous employment. For this purpose, I integrate the approaches of Chirikos and Nestel (1985) with those of Jacobson, LaLonde, and Sullivan (1993). I assume that the timing of a layoff or the onset of a sufficiently severe chronic condition that causes a worker to separate from her employer is a largely unanticipated event. Yearly indicator variables, L^m and H^m, denote the time duration since either a layoff or ill-health separation occurred. These enable the parsing of the lingering impacts of these exogenous shocks by capturing the effect of a displacement that occurred m years in the past, where $m = 1, 2, 3, 4, 5$, and more than 5 years ago. Layoff and disability coefficients, $\gamma_{\cdot L_m}$ and $\gamma_{\cdot H_m}$, capture the enduring effects of dislocation.

Hours are also regressed upon the logarithm of the real hourly wage rate, which is endogenous, and so in order to obtain consistent estimations of the coefficients in this model, cross-equation correlations of the heterogeneity terms must be permitted. The individual random effects in the jointly estimated model are normally distributed as

$$\begin{pmatrix} \theta_i \\ \alpha_i \end{pmatrix} \sim N\left(0, \begin{bmatrix} \sigma_\theta^2 & \\ \sigma_{\theta\alpha} & \sigma_\alpha^2 \end{bmatrix}\right),$$

[8]Experience, industry division, and type of employment are excluded in the hours equation.

and the job heterogeneity terms are distributed as bivariate normal random variables

$$\begin{pmatrix} \varphi_{ij} \\ \chi_{ij} \end{pmatrix} \sim N\left(0, \begin{bmatrix} \sigma_\varphi^2 & \\ \sigma_{\varphi\chi} & \sigma_\chi^2 \end{bmatrix}\right).$$

The time-varying residuals are independently and identically distributed normal random variables given by

$$\varepsilon_{ijt} \sim N\left(0, \sigma_\varepsilon^2\right),$$

and

$$\eta_{ijt} \sim N\left(0, \sigma_\eta^2\right).$$

1.3.2 Spousal Job Displacements

The manner in which an exogenous shock to one's partner induces changes in the economic behaviors of the other member in the couple is next addressed. Spousal compensation for the unanticipated job loss is manifested by job transitions, as well as by changes in hourly wage rates and hours spent at work. I compare the duration of the current spell of employment for those married workers with spouses who have been displaced because of a layoff or a disabling condition with the length of employee-employer attachments of those married workers who are employed but do not have spouses who have experienced either type of forced separation by using the proportional hazard given by

$$\begin{aligned} \ln h(t_{ij}) &= T(t_{ij})\gamma + X_i'\beta_{Z1} + X_{it}'\beta_{Z2} + X_{ij}'\beta_{Z3} + \\ &\quad \sum_{m=1} \gamma_{ZL_m} L_{it}^m + \sum_{m=1} \gamma_{ZH_m} H_{it}^m + \nu_i. \end{aligned}$$

This proportional hazard enables me to model the transition rate out of employment and relate this to previous job dislocations the spouses of the married workers have endured. It is associated with the survivor function

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

and probability density function

$$f_E(t_{ij}) = h(t_{ij})S(t_{ij}).$$

I assume that the separations induced by the layoff or disability of the spouse of a worker are exogenous events. Coefficients of the indicator variables that are denoted by L^m and H^m provide knowledge of the lasting impact that spousal separations relating to layoff and ill-health have upon the economic outcomes of their partners. These indicator variables capture the effect of spousal displacements that occurred m years in the past, where $m = 1, 2$, and more than 3 years ago. The probability of a married worker with a spouse who has suffered a job separation remaining with a job relative to this probability for an otherwise identical individual is obtained through estimates of γ_{ZL_m} and γ_{ZH_m}. These coefficients are interacted with gender to capture the lasting impacts of the spouse of the worker experiencing unemployment caused by layoff or ill health.

Additional regressors in the hazard include $T(t_{ij})$, a piecewise-linear spline of the months of current employment for married worker i at job j ; X_i, a vector that is composed of gender, race, education groups, and ethnicity; X_{it}, a vector of time-varying characteristics that include the number of children in the household and the interaction of gender with the number of children in the household; X_{ij}, a vector of static employee-employer match characteristics consisting of union status, industry division, and type of employment; and finally piecewise-linear splines of age, labor force experience, and calendar time. SIPP panel year variables are also included in the specification. Heterogeneity is controlled for in the hazard model by including the random effect ν_i that is independently and identically distributed as $N(0, \sigma_\nu^2)$.

To explore the quantities that the employees with spouses who have experienced a separation work and earn as compared to before the displacement of their marital partners, I proceed to jointly estimate a regression of the logarithm of the real hourly wage rate and a regression of the logarithm of weekly hours conditional on employment that is consistent with equations (1.2) and (1.2) above. In this specification, the shock indicators are those of the worker's spouse instead of the worker herself.

1.3.3 Likelihood Functions

I simplify the notation in equations (1.2) and (1.2) in order to consider the form of the likelihood I am estimating. I allow the logarithm of the real wage rate to be represented by

$$\begin{aligned} W_{ijt} &= X_W' \beta_W + \theta_i + \varphi_{ij} + \varepsilon_{ijt} \\ &= X_W' \beta_W + \xi_{ijt}, \end{aligned}$$

and the estimation of the logarithm of weekly hours conditional on employment by

$$R_{ijt} = X_R' \beta_R + \alpha_i + \chi_{ij} + \eta_{ijt}.$$

The likelihood function of the joint model of hours and the wage rate is the product of the marginal probability of wages and the probability of hours conditional on wages:

$$\begin{aligned}
&P(W_{ijt}, R_{ijt}|\beta_W, \beta_R, , \sigma_\varepsilon^2, \sigma_\eta^2, \sigma_\theta^2, \sigma_\alpha^2, \sigma_{\theta\alpha}, \sigma_\chi^2, \sigma_\varphi^2, \sigma_{\varphi\chi}) \\
= &\int_\alpha \int_\chi f_W(W_{ijt}|\beta_W, \Sigma_{\xi\xi}) f_R(R_{ijt}|\beta_R, \sigma_\eta^2, \alpha, \chi, W) \times \\
&f_\chi(\chi|\sigma_{\chi|W}^2, W) f_\alpha(\alpha|\sigma_{\alpha|W}^2, W) d\chi d\alpha
\end{aligned}$$

$$\begin{aligned}
L_i \;=\; & (2\pi)^{-\frac{T_i}{2}} |\Sigma_{\xi\xi}|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(\vec{W}_i - X_W'\beta_W)' \Sigma_{\xi\xi}^{-1} (\vec{W}_i - X_W'\beta_W)\right\} \times \\
& (2\pi)^{-\frac{T_i}{2}} (\sigma_\eta)^{-T_i} \int_\alpha \phi\left(\frac{\alpha_i|\vec{W}_i}{\sigma_{\alpha|\vec{W}_i}}\right) \int_\chi \prod_{j=1}^{J_i} \phi\left(\frac{\chi_{ij}|\vec{W}_i}{\sigma_{\chi|\vec{W}_i}}\right) \times \\
& \prod_{t=1}^{T_{ij}} \exp\left\{-\frac{1}{2}\left(\frac{R_{ijt} - X_R'\beta_R - \alpha_i - \chi_{ij}}{\sigma_\eta}\right)^2\right\} d\chi d\alpha,
\end{aligned}$$

where J_i is the total number of jobs each worker holds during the panel, T_{ij} is the number of time periods each employee-job match endures,

$$T_i = \sum_{j=1}^{J_i} T_{ij}$$

is the total number of time periods each worker is employed at all jobs,

$$\vec{W}_i = \left\{\{W_{ijt}\}_{t=1}^{T_{ij}}\right\}_{j=1}^{J_i}$$

is the vector of wages over all jobs and time periods for individual i, $\Sigma_{\xi\xi}$ is the covariance matrix of the T_i-vector of residuals for the hourly wage equation, and $|\Sigma_{\xi\xi}|$ is its determinant. The random person effects are identified by the monthly observations of each individual, while the random job match effects are identified by repeated observations associated with that particular job.

For married couples, I allow the proportional hazard function to be represented by

$$\ln h(t_{ij}) = X_Z'\beta_Z + \nu_i.$$

The likelihood of the hazard is then given by

$$P(t_{ij}|\beta_z, \sigma_\nu^2) = \int_\nu f_E(t_{ij}|\beta_Z, \nu) f_\nu(\nu|\sigma_\nu^2) d\nu$$

$$L_i = \int_\nu \phi\left(\frac{\nu_i}{\sigma_\nu}\right) \prod_{j=1}^{J_i} \left\{ [h(t_{ij}|\beta_Z)]^{D_{ij}} S(t_{ij}|\beta_Z) \right\} d\nu,$$

where J_i is the total number of jobs for that individual and

$$D_{ij} = \begin{cases} 1, \text{ if the employment spell ends} \\ 0, \text{ if the employment spell is censored} \end{cases}.$$

Each spell of employment consists of a period of uninterrupted job attachment during which time the worker receives monthly pay. These spells can terminate due to the layoff of an individual, a severe health event that causes the employee to part ways with the employer, or the decision of a worker to transition into a new employment situation or to enter into non-employment. The random person effect is identified by the existence of multiple job spells for each worker.

1.4 Data

1.4.1 Survey of Income and Program Participation

The Survey of Income and Program Participation covers the population of noninstitutionalized civilians residing in America. It is a multipanel, longitudinal survey conducted by the U. S. Census Bureau, with each panel spanning between 2.5 and 4 years. Between 14,000 and 36,700 households are selected to be interviewed in each panel of the survey. Household members who are at least 15 years old are interviewed once every four months for the duration of the panel about their employment, program participation, and income. Topical modules supplement the core wave questionnaires by providing more detailed information about past labor force participation, demographic characteristics, disability, and additional sources of income. In this way, the SIPP serves to measure the economic situations of Americans. This study makes use of the 1990-1993 panels in which the possible reasons for work cessation include layoff and a means to derive knowledge of health-related separations.

While the Health and Retirement Study has been used in a number of papers to explore the implications of disability, the construction of the baseline HRS sample restricts the age of those examined to heads of households aged 51-61 and their spouses. An increasing number of younger workers are becoming impaired, however, and it is only with a longitudinal data set such as the SIPP that it is possible to model the behavior of younger cohorts who have experienced exogenous health shocks that have resulted in separations from the work force. With such a sample, it is also possible to derive estimates without concerns that the results might easily be confused by retirement behaviors.

Construction of Indicators of Exogenous Separation

The longitudinal structure of the SIPP panels enables the creation of indicators that are representative of the number of years that have passed since an exogenous shock induced the dissolution of an employee-employer pairing. The Employment History topical module contains detailed questions about former positions. Respondents are able to specify the month and year in which they ended an earlier job and whether the main reason they stopped working for this employer is related to either health or layoff. Furthermore, a second set of questions probes into periods lasting at least 6 months that the individual has spent out of the work force. Own illness or disability are listed among the reasons for these gaps in employment along with the years that span these absences. Potentially, one indicator of past separation due to layoff and up to two indictors of past separation due to poor health can be obtained from this topical module along with the timing of these events.

In the Labor Force and Recipiency core wave questionnaires, those whose work has terminated during the reference period are asked to specify a reason. In this manner, evidence of contemporary separations is collected as time progresses through the longitudinal SIPP panels. The possible explanations for job cessation include being laid off, choosing to retire, being discharged, having been at a temporary job that ended, accepting another job opportunity, and quitting for some other reason. This last option is used in combination with an indicator of wellness to determine when an exogenous health shock has forced a worker to separate from her place of employment.

Care is taken to ensure that exits are in fact exogenous shocks to the employed individual. The Worker Adjustment and Retraining Notification (WARN) Act, effective beginning in February 1989, requires that employers of 100 or more employees provide 60 days of advanced notice of mass layoffs and plant closures so that workers can prepare for the impending dislocation. Thus, a layoff is not included in the list of exit dates if the worker smoothly transitions between jobs during the course of the panel or if she is recalled.[9] Similarly, since severe impairments

[9]A smooth work transition occurs when employment is overlapping and continuous or when the individual has found reemployment within four days of the date of job termination. Stinson (2003) at the U. S. Census Bureau performed extensive research using name matching software to create an internal use SIPP jobs file that corrects the job identifiers across waves. Since displacements are defined as events that result in the permanent conclusion of a job match, a worker who was rehired following a layoff by her previous employer is not flagged as having been separated from this position even if the individual has indicated within the survey that she was laid off.

would likely impact all jobs held if a sudden health shock occurred, an ill-health exit date is deleted when it is apparent that a smooth transition between jobs has occurred. This measure should further improve the quality of the indicators of disability dislocations.

The wellness variable is acquired from several sources to ensure that it is accurately representative of the individual's perceived current status, with information from the topical modules supplementing the core wave files. The Work Disability History topical module, the Functional Limitations and Disability topical module, the Medical Expenses and Work Disability topical module, and the Labor Force and Recipiency core wave files all contain questions about disabling conditions. If a respondent claims that her health or condition limits the kind or amount of work that can be done;[10] if she has a physical, mental, or other health condition which limits the kind or amount of work that can be done;[11] if she claims to have been employed when a work-limiting disability began;[12] or if her health condition prevents her from working at a job or business,[13] then a wave-level disability variable is flagged. Temporary illnesses that are revealed by follow-up questions to non-permanent job separations are not included in this measure, regardless of duration.

Relying on self-reported measures as true indicators of work-limiting disabilities is somewhat problematic due to the fact that the associated measurement error is likely nonrandom. For example, the use of medical facilities tends to increase with

[10] Work Disability, Functional Limitations and Disability, and Medical Expenses and Work Disability topical modules.

[11] All sources.

[12] Work Disability topical module.

[13] Functional Limitations and Disability, and Medical Expenses and Work Disability topical modules.

income despite the fact that those who are in higher wage brackets tend to also be of better health. As a result, this group is more educated about various illnesses they might have and are more likely to report them (Currie and Madrian 1999). In addition, unemployed individuals may be inclined to exaggerate poorer health status in an attempt to justify their lack of work (Butler, Burkhauser, Mitchell, and Pincus 1987).

To further complicate these matters is the issue of the interpretation of questions regarding health status or condition. Respondents who indicate that they have a health problem or that they are limited in the kind or amount of work they can perform may suffer from disability, disease, illness, substance abuse, brief ailments, or psychological impairments. On the other hand, some disabilities may not hinder one's capacity to accomplish assigned tasks in the current place of work, but may restrict the choice set of occupations available. These differing categories of workers may be induced to answer survey questions regarding disability status identically, while the dissimilarities of the base issues could confuse the derived results of a focused study.

1.4.2 Social Security Administrative Records

Ideally, a measure based on clinical evaluations of health status is desired. This is because such an indicator enables the researcher to separate acute, but ephemeral medical conditions that have few long-lasting economic consequences from illnesses that continually plague a person, having a cumulative effect that are detrimental to future economic outcomes. The Social Security Administration has provided benefits data from the 831 Disability and Master Beneficiary Records for the 1990-1993 panels of the SIPP that allow such a distinction to be made. In addition, an exact match earnings file for these panels, known as the Summary Earnings Records, is available from which knowledge of Social Security Disability Insurance program eligibility is derived.

831 Disability

The 831 Disability (F831) master file contains data on the Disability Determination Services' (DDS) decisions regarding applications and subsequent appeals for disability benefits under Titles II and XVI of the Social Security Act. Titles II and XVI detail the Social Security Disability Income (SSDI) and Supplemental Security Income (SSI) programs, respectively. Eligibility requires that a person be unable to perform any kind of substantial gainful work[14] because of a physical or mental impairment (or a combination of impairments). These conditions must be expected either to last a continuous period of at least 12 months or to eventually result in death. Applicants must be able to verify that they are not gainfully employed and also must have a complete medical evaluation so that the primary diagnosis codes for their ailments can be appropriately supplied to the DDS for review.

Only F831 records with dates of decision for awards beginning in 1989 are available, but these have initial dates of application, appeal, and disability onset that can be from years prior. To correct the left censoring of F831, historic information from the Social Security Administration's Master Beneficiary Records (MBR) are integrated into this study.

[14]Substantial gainful activity is defined as employment in which earnings average more than a fixed monthly amount. In 2005, this total is $830.

Social Security Disability Income Title II allows for the Social Security Disability Income program by outlining federal old-age, survivors, and disability insurance (OASDI) benefits. SSDI provides federal disability insurance benefits for workers who have become disabled or blind before the age of retirement after having contributed to the Social Security Trust Fund. Upon the retirement, disability, or death of a fully insured worker, spouses with disabilities and dependent children of the primary beneficiary are also eligible for disability benefits.

Fully insured workers have recent covered work, which translates into having been employed for 20 of the last 40 quarters, or half of the previous 10 years. Exceptions to this requirement are made for those who become disabled early in their job histories. If impaired before 31, the amount of time in the work force should be half of the time since age 21. In addition to being fully insured and having the necessary medical documentation of the work-limiting condition, to qualify for DI benefits the applicant must also be disability insured. This means she must have worked for about one-fourth of the time elapsing after age 21 and up to the year of disability.

A waiting period of five months[15] must elapse before SSDI benefits are administered according to the guidelines of this program. The philosophy behind this required delay is that it discourages individuals who do not have long-term disabilities from receiving payments from multiple sources during the early months of their conditions. Often with transitory illnesses, private disability plans and employer sick pay provide sufficient resources until the worker becomes able-bodied and is capable of resuming employment. SSDI is intended to assist only those with grave illnesses or conditions and the waiting period induces only these people to

[15]The 1972 Amendments to the Social Security Act reduced the waiting period for benefits from six months to five.

apply.

Supplemental Security Income The Supplemental Security Income program was established under Title XVI of the Social Security Act and is a federally administered cash assistance program that is financed by general tax revenues. SSI aids individuals who are at least 65 years of age, blind, or disabled and who demonstrate sufficient income and resource limitations.

SSI and SSDI have essentially the same set of disability requirements [16] that must be satisfied in order to receive income resulting from disability, but those seeking benefits from the former source must also satisfy a family means-test of income. A person can be eligible for SSI benefits even if she has never worked or paid taxes under the Federal Insurance Contribution Act, which is not the case with SSDI. If, on the other hand, the person is fully insured and disability insured with inadequate assets, it is possible for her to simultaneously receive income from both sources. Due to the difficulty involved in determining eligibility for SSI combined with the knowledge that any fully insured worker with limited resources would apply for both types of benefits from SSA, the study of hours and wages is restricted to those with Title II eligibility.

Master Beneficiary Records

The Master Beneficiary Records are used by SSA to administer OASDI payments. In the case of disability insurance, the primary beneficiary[17] is listed along with

[16]The applicant must exhibit no substantial gainful employment and must provide evidence of compromising medical conditions that are anticipated to either result in death or persist at least a period of one year.

[17]The primary beneficiary is the worker upon whose earnings the benefit entitlement exists.

an array of dates of disability onset, the corresponding dates of filing and decision, and the outcome of the adjudication process. Any individuals who have applied for benefits have a record generated when the application is decided as an award, a disallowance, an abatement, or is withdrawn. An advantage of the use of this file is that a history of onset dates of disabling conditions are revealed along with dates of entitlement to disability payments.[18]

Summary Earnings Records

Sample-limiting restrictions will be imposed on the SIPP panels to include only those who would be eligible to apply for SSDI benefits when including health variables extracted from the benefits records in the estimations. Since a goal of this paper is to utilize not only survey data, but also benefits data from the Social Security Administration, it will be important to select a group of individuals who would be capable of applying for SSDI benefits upon the onset of a serious condition.

The Summary Earnings Records are topcoded at the taxable maximum each year, and contain yearly information on earnings from 1951 onward. Estimates of total quarters worked for the period between 1937 and 1952 exist on this file, as well. Covered quarters of work are recorded from 1951 until 1977, whereafter they are imputed by SSA based upon earnings thresholds. This history enables the yearly derivation of the number of quarters of coverage so that the calculation of fully insured and disability insured status for each individual is possible.[19] Since

[18]The date of entitlement to disability is the month and year in which the individual is first entitled to disability benefits. The date may be retroactively set up to 12 months before the date of filing because it is meant to accurately reflect the date that DI benefits should have started.

[19]Essentially, this calculation is reduced to the following: if the individual is

only those workers who meet the set of standards outlined by the Social Security Administration are candidates to receive disability benefits, limiting the SIPP panels to individuals who are both fully and disability insured provides a restricted sample that can be used to compare the quality of the demographic measures with those found within administrative data sources.

Creating this subset serves a dual purpose. Primarily, the adverse health of these covered workers should be evident in both the demographic survey and benefits records for sufficiently severe maladies, such as ailments that would induce a worker to unexpectedly part ways with her employer. Additionally, this reduced population of workers now consists purely of a highly attached work force. This is key in analyzing exogenous separations, as researchers have traditionally considered displaced workers as those with at least three years of tenure (Fallick 1996). By reducing the sample to employed individuals with sufficient quarters of coverage to be considered both fully and disability insured, I introduce an alternative definition of highly attached workers.

SSDI Applicants

It is necessary to remark upon active workers who have records of medically diagnosed ailments in the benefits records. Essentially, only three means exist by which an individual stops receiving DI benefits: death, recovery (including those who voluntarily return to work and those who reluctantly do so after the termination of their payments following a medical review), and transference to the retirement program. Within the 1990-1993 SIPP panels, it was less common for individuals

less than 32 years of age, then she needs to have worked half of the time that has elapsed since age 21; if the individual is 32 or older, then she needs to have worked one-fourth the time that has elapsed since age 21 and one-half of the previous ten years.

to become well and choose to leave the DI rolls.[20] Mainly for this reason, those who are employed in the SIPP and who have evidence of impairments acquired from either the F831 or MBR are most likely to be rejected applicants.[21]

Statistics on the percentage of applications that are rejected vary. Social Security Administration (2003) statistics indicate that in the early 1990s, between 43.8% and 47.7% of those who filed claims received awards. However, these are crude rates that were not calculated using edited data, may contain duplicate cases, and are additionally based on the number of applicants in the same year as the awards.[22] The Social Security Advisory Board (1998) presents more detailed estimates of award rates: 32% of initial applications, and 15% of the 50% that are reconsidered by DDS are added to the DI rolls. Of the 25% of individuals who pursue their denied claims, only a small fraction are eventually granted benefits by an administrative law judge, an appeals council, or by federal court decisions. Refiling, appealing a rejected application, or otherwise continuing to engage in the disability determination process requires that the individual remain absent from the labor force. As such, the workers with evidence of health events in the restricted SSA sample are those who have resigned themselves to the idea that despite their own beliefs about the severity of their impairments, the DDS is of the opinion that they are capable of gainful employment.

[20]The creation of a program under the Ticket to Work and Work Incentives Improvement Act of 1999 was phased in over a 3-year period to encourage those receiving SSDI and SSI to become self-sufficient. Prior to this, and within the scope of this study, workers on the disability rolls who considered taking a trial period to test out their ability to partake in gainful activities risked losing their benefits indefinitely.

[21]Imposed age restrictions exclude workers who might have once received benefits but were transferred to the retirement program when they turned 65.

[22]A casual perusal of the F831 reveals that it is frequently the case that applications are approved that were filed in a year that differs from the year of the award.

Precise dates of disability onset from the benefits records are used to establish an alternate set of indicators of health-related shocks out of employment. The timing of the onset of a grave disability that results in the dissolution of a job is specified by a medical doctor on applications for SSDI. When missing, I choose to use the filing date in its place, followed by the date of decision less 4.5 months, which is the average duration of DDS deliberation in the panels. From these dates, administrative verification of the existence of functional limitations is derived. Only shocks occurring after the earliest date of impairment from F831 and MBR records that do not have another reason specified in the SIPP for the job cessation become SSA health shocks. Of those with a primary diagnosis code for their disability on the MBR, 80.4% have a physical impairment, 16.3% have a mental illness, and 3.3% suffer from mental retardation.

1.4.3 Methodology

The data sources previously detailed are integrated into the models I have presented. Each is estimated using both the layoff and disability separation indicators representing the time that has elapsed since the exogenous displacement shock occurred. All known displacements will be tracked in the joint hours and wage model following Stevens (1997). The 1990-1993 SIPP panels are combined for this purpose. The SIPP topical modules and core wave files provide the necessary information regarding the reason for job termination.

The models are then estimated using responses about layoff displacement from the demographic survey and the timing of disability onset acquired from integrated SSA benefits data files. In the examination of their own displacements, only those workers who would be eligible to apply for SSDI benefits if a disabling condition were to occur during their current period of employment will be included. It is assumed that with this set of individual workers, anyone who truly becomes disabled would indeed be induced to apply for benefits and a record of this action would appear in the administrative data. In making this restriction for the comparison of survey health indicators with those found in administrative files, I limit the sample to those who are highly attached to the work force which is consistent with previous research that examines the lingering impacts of separations.

In exploring spousal reactions to a job dislocation within a couple, a similar methodology is followed. However, because it is necessary to consider the marginal workers who may have entered the labor force, in utilizing health measures from the administrative data sources, the sample is restricted to those workers with spouses who are eligible to apply for SSDI benefits. This permits a comparison of the administrative and survey measures of health when the spouse is disabled. Thus, the subset of workers included in the estimation are not themselves highly attached, but their spouses are.

1.5 Results

1.5.1 Own Job Displacements

The joint model specification is evaluated with two samples, the first of which is the group of all workers in the stacked 1990-1993 SIPP panels. This collection of individuals is referred to as the unrestricted sample. The second is the set of workers who have both a verified Social Security Number assigned to their SIPP identification number and who are deemed eligible to apply for Social Security Disability Insurance should a debilitating condition occur in the given month. These people are more highly attached to the labor force and thus comprise the restricted sample.[23] Within this limited sample, both demographic and administrative health measures are utilized to determine whether the reason for leaving a position is related to an exogenous health shock. Layoff information is derived solely from the SIPP.

Summary statistics concerning worker and job characteristics are presented in Table 1.1 for the two samples. The unrestricted subset consists of 34,906 individuals and 62,507 employee-employer matches while 28,164 people and 50,833 jobs comprise the restricted survey sample. The two groups do not differ greatly in their population means. The highly attached work force has a slightly larger number of individuals who have attended some college courses, marginally fewer children, and 1% fewer people have health insurance coverage under another's plan. Additionally, the hourly wage rate is $0.20 greater than that of the average worker in the full sample.

The timing of exogenous shocks is outlined in Table 1.2 for layoff, SIPP health, and SSA health shocks. Layoffs are the most common type of displacing event. Dislocations derived from survey-based measures of health are the next most frequent in the data. These measures are summarized only for those who are employed. Characteristic of these statistics is a dampening in the percentage of displacements over the years.

In comparing the incidence of the two types of health shocks, Table 1.3 exhibits for the restricted sample the percentages of ever-reported health limitations in the

[23]Excluded from both sets of workers are household workers, armed forces personnel, unemployed military personnel, those with job spans lasting less than one day, those with allocated responses, those younger than 21 or older than 60, those with weekly hours less than or equal to zero or a real hourly wage of less than $0.10, and those who are not original sample members.

Table 1.1: Worker and Job Summary Statistics

	Unrestricted Sample			Restricted Sample		
	Obs	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Worker Characteristics:						
White	34,906	0.8539	23.3137	28,164	0.8649	22.6529
Hispanic	34,906	0.0913	19.0098	28,164	0.0834	18.3207
Male	34,906	0.4897	32.9985	28,164	0.5121	33.1207
Education:						
Years	34,906	13.2573	181.1480	28,164	13.3062	177.6184
High School	34,906	0.3316	31.0770	28,164	0.3314	31.1903
Some College	34,906	0.2977	30.1843	28,164	0.3077	30.5834
College Degree	34,906	0.1191	21.3804	28,164	0.1221	21.6936
Graduate Schooling	34,906	0.1205	21.4915	28,164	0.1180	21.3774
Time-Varying Worker Characteristics:						
Married	835,852	0.6164	33.0757	696,782	0.6134	33.2157
Number of Children	835,852	1.0063	80.3016	696,782	0.9728	79.0392
Health Insurance Under Another's Plan	835,852	0.1885	26.6054	696,782	0.1782	26.1021
Job Characteristics:						
Number of Jobs	62,507	1.8189	76.7921	50,833	1.8330	77.6084
Union Member	62,507	0.1600	24.1260	50,833	0.1570	23.9809
Job Type:						
Private, Not-for-Profit, Tax Exempt, or Charitable	62,507	0.1371	22.6373	50,833	0.0574	15.3314
Government	62,507	0.1544	21.8843	50,833	0.1176	21.2379
Industry:						
Agriculture and Forestry/Fisheries	62,507	0.0177	8.6883	50,833	0.0167	8.4515
Mining	62,507	0.0048	4.5363	50,833	0.0053	4.7775
Construction	62,507	0.0663	16.3784	50,833	0.0682	16.6157
Manufacturing	62,507	0.1551	23.8212	50,833	0.1647	24.4479
Trans., Comm., and Public Utilities	62,507	0.0558	15.1011	50,833	0.0565	15.2241
Wholesale Trade	62,507	0.0374	12.4829	50,833	0.0401	12.9305
Retail Trade	62,507	0.1976	26.2052	50,833	0.1946	26.0972
FIRE	62,507	0.0583	15.4230	50,833	0.0609	15.7650
Business and Repair Services	62,507	0.3684	31.7433	50,833	0.3597	31.6372
Public Administration	62,507	0.0362	12.2915	50,833	0.0312	11.4616
Time-Varying Job Characteristics:						
Hourly Wage ($2003)	835,852	15.06	1,363.50	696,782	15.26	1,380.99
Weekly Hours	835,852	38.4000	793.2878	696,782	38.8921	776.0856
Months of Experience	835,852	190.8291	7,355.7900	696,782	190.8158	7,307.7000

Table 1.2: Summary of the Timing of Exogenous Shocks

	Unrestricted Sample		Restricted Sample	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Own Exogenous Layoff Shock:				
0-1 Year Ago	0.0741	17.8172	0.0759	18.0652
1-2 Years Ago	0.0295	11.5011	0.0304	11.7188
2-3 Years Ago	0.0265	10.9277	0.0275	11.1486
3-4 Years Ago	0.0179	9.0210	0.0187	9.2509
4-5 Years Ago	0.0112	7.1657	0.0117	7.3477
5+ Years Ago	0.0376	12.9370	0.0393	13.2593
Own Exogenous SIPP Health Shock:				
0-1 Year Ago	0.0222	10.0207	0.0214	9.8689
1-2 Years Ago	0.0050	4.8144	0.0048	4.7311
2-3 Years Ago	0.0038	4.2031	0.0037	4.1665
3-4 Years Ago	0.0028	3.5978	0.0026	3.5010
4-5 Years Ago	0.0019	2.9837	0.0018	2.8545
5+ Years Ago	0.0063	5.3646	0.0059	5.2340
Own Exogenous SSA Health Shock:				
0-1 Year Ago	-	-	0.0088	6.3859
1-2 Years Ago	-	-	0.0012	2.3155
2-3 Years Ago	-	-	0.0008	1.9047
3-4 Years Ago	-	-	0.0004	1.3935
4-5 Years Ago	-	-	0.0003	1.2489
5+ Years Ago	-	-	0.0015	2.6331

SIPP and SSA data along with the mean weekly hours and hourly wage rates for these cells. Those without any history of an ailment from either source (94.41%) have the highest mean weekly hours and hourly wage rates. Curiously, 0.63% have contacted the Social Security Administration to report their health limitations without claiming to have any such difficulties in the SIPP. The mean wage rate of these individuals is \$4 less than that of those who never claimed either type of health problem. Those with consitent reports of past illness (1.27% of the sample) work 3.53 fewer hours each week on average and earn an hourly rate that is \$5.76 less than those whose SIPP and SSA records indicate that they are healthy.

Trends in the means of the hourly wage rate and weekly hours in Table 1.4 are similar in the restricted and unrestricted samples, but the magnitudes of these values are moderately larger in the subset of more highly attached workers. Figures 1.1 and 1.2 illustrate the manner in which these statistics reveal the enduring

Table 1.3: Ever-Reported Health Limitations in the SIPP and SSA Data

		SSA Health	
SIPP Health		**No**	**Yes**
No	**Percentage**	94.41%	0.63%
	Mean Weekly Hours	38.97	38.27
	Mean Hourly Wage Rate	$15.46	$11.46
Yes	**Percentage**	3.69%	1.27%
	Mean Weekly Hours	37.52	35.44
	Mean Hourly Wage Rate	$10.80	$9.70

implications of job displacements, a theme that will appear again later in analyzing the joint model specification. Highly attached employees who have never experienced a displacement approximately earn a wage rate of $15.50 and work just under 39 hours each week. After reemployment following a firm shock, the average wage rate is $13.72 and weekly hours rise. Those with ailment-related job separations are economically harder hit by displacements: new positions within the first twelve months of their recovery are on average found at a the lower rate of around $10.50. After one year, these wages fall even further. This may be evidence that those whose job searches were more lengthy eventually chose to accept low offers.[24] Hours of those with impairments plummet over the years, eventually dropping to 30.56 by the end of the fifth year since the initial date of exit according to SSA health measures.

Table 1.5 presents Pearson correlation coefficients for the health shocks based upon survey measures of disability and those derived from medial records obtained from the Social Security Administration. The correlation coefficients of these measures range from 33.6% to 43.7%. While these are lower than one might expect, they are consistent with the findings of Baker, Stabile, and Deri (2004). In match-

[24]Stevens (1997) and Kletzer and Fairlie (2003) also find a depression in the wage rate after a few years have passed since an event of dislocation.

Table 1.4: Means of Hourly Wage and Weekly Hours

	Unrestricted Sample			Restricted Sample		
	Hourly Wage	**Weekly Hours**	**% Displaced**	**Hourly Wage**	**Weekly Hours**	**% Displaced**
Own Exogenous Layoff Shock:						
No Shock	$15.48	38.26	-	$15.68	38.78	-
0-1 Year Ago	$13.28	38.94	0.5036	$13.72	39.37	0.4993
1-2 Years Ago	$11.94	37.98	0.1387	$12.06	38.24	0.1388
2-3 Years Ago	$12.33	38.55	0.1033	$12.40	38.70	0.1035
3-4 Years Ago	$12.90	38.91	0.0638	$13.13	39.29	0.0648
4-5 Years Ago	$12.67	39.75	0.0417	$13.06	40.27	0.0423
5+ Years Ago	$14.80	39.70	0.1490	$15.19	40.22	0.1513
Own Exogenous SIPP Health Shock:						
No Shock	$15.25	38.48	-	$15.45	38.96	-
0-1 Year Ago	$10.46	36.81	0.5448	$10.72	37.51	0.5469
1-2 Years Ago	$10.04	36.68	0.0877	$10.30	37.53	0.0846
2-3 Years Ago	$9.74	35.48	0.0717	$9.88	36.65	0.0707
3-4 Years Ago	$10.11	35.08	0.0570	$10.47	36.19	0.0556
4-5 Years Ago	$10.14	34.72	0.0413	$10.30	35.40	0.0410
5+ Years Ago	$11.22	36.55	0.1975	$11.49	37.52	0.2012
Own Exogenous SSA Health Shock:						
No Shock	-	-	-	$15.32	38.92	-
0-1 Year Ago	-	-	-	$10.45	37.49	0.6720
1-2 Years Ago	-	-	-	$9.59	35.98	0.0603
2-3 Years Ago	-	-	-	$9.44	35.16	0.0402
3-4 Years Ago	-	-	-	$11.00	32.36	0.0312
4-5 Years Ago	-	-	-	$8.37	30.56	0.0324
5+ Years Ago	-	-	-	$11.50	35.57	0.1639

Note: Workers with more than one event of the same type were excluded from the calculation of these statistics.

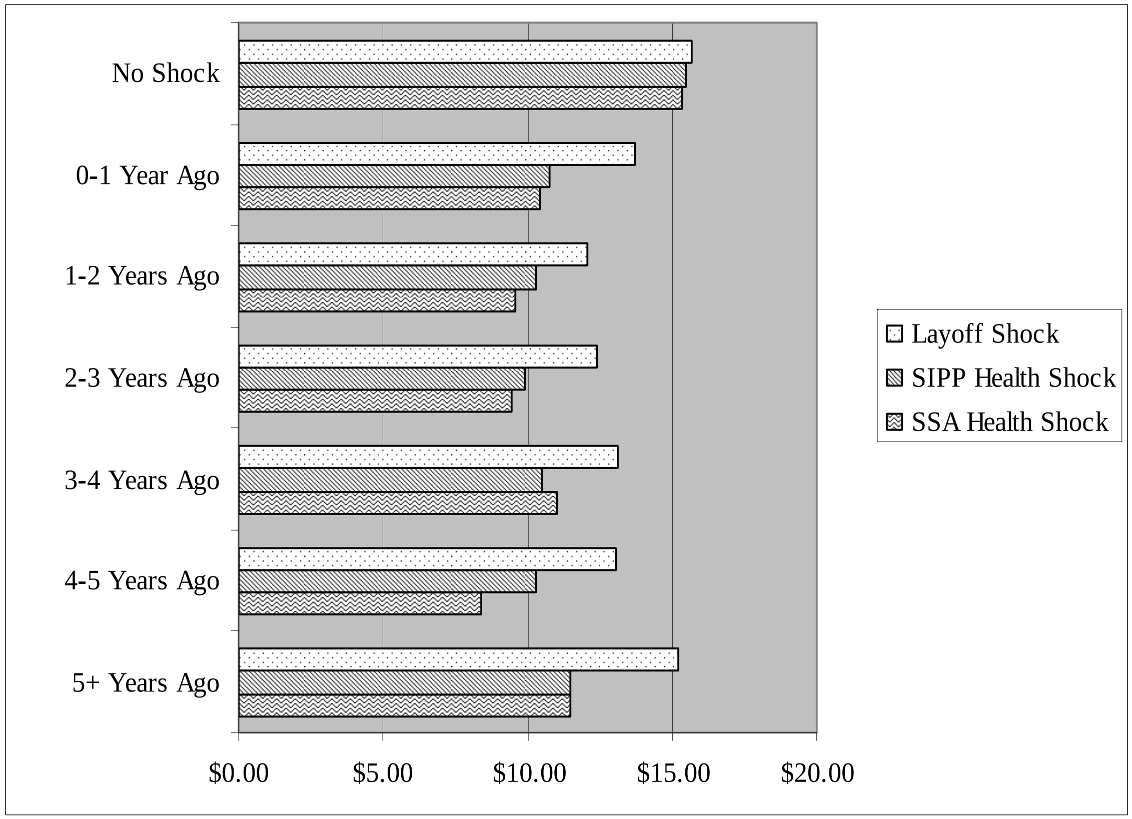

Figure 1.1: Mean Hourly Wage Rate

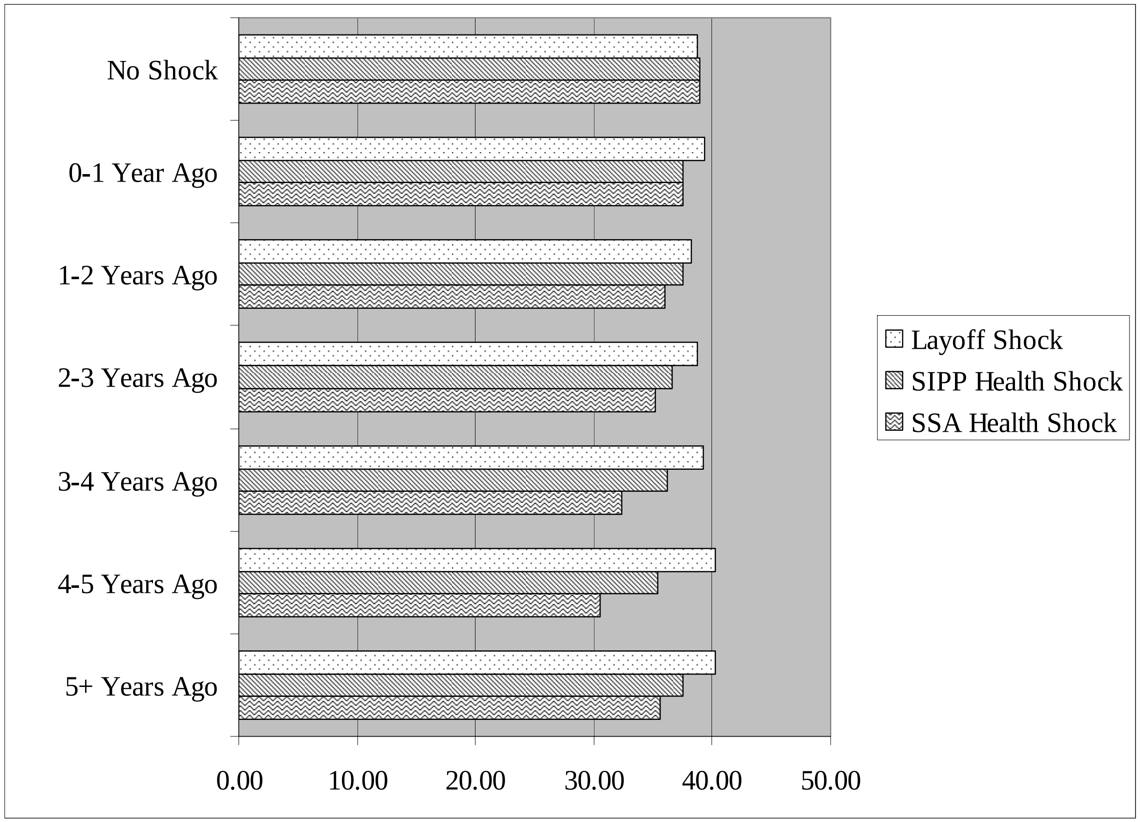

Figure 1.2: Mean Weekly Hours

ing the 1994 Canadian National Population Health Survey to the Ontario Health Insurance Plan data in order to validate the self-reported health measures in the survey data with diagnosis and treatment information from the public health care system, the authors found that the correlation coefficients for only three of the thirteen conditions studied was above 50%. Even for serious medical conditions such as cancer, strokes, and back problems, correlations were 46.9%, 47.9%, and 23.1%, respectively.

Understandably, not all people who experience the sudden onset of work-limiting disabilities who are concurrently eligible for SSDI would choose to apply for benefits unless they expected their condition to result in either death or a spell of at least twelve months out of the work force. While the survey measures of health are more sensitive to errors of justification and measurement, they are also likely tracking events that while substantial, are not severe enough to impede eventual recovery. Only dire ailments should induce an unhealthy individual to go through the lengthy process of submitting an application for review by the Disability Determinations Services, as this action requires at least a five month commitment to labor force inactivity which is a considerable risk for those who believe they are unlikely to be awarded DI benefits.

Another reason why the SIPP- and SSA-based measures are not more highly correlated could be related to the issue of timing. People may have chronic conditions that they would readily report in the survey, but only years after a particularly severe health episode might such a report appear in the administrative records. Thoughts of one's future economic situation may only arise after a period of improved and stabilized health. This delay in the original date of disability onset and the date of filing may contribute to the inconsistencies in these measures.

Table 1.5: Pearson Correlation Coefficients for SIPP- and SSA-based Health Shocks

	SIPP Health Shock					
SSA Health Shock	**0-1 Year Ago**	**1-2 Years Ago**	**2-3 Years Ago**	**3-4 Years Ago**	**4-5 Years Ago**	**5+ Years Ago**
0-1 Year Ago	**0.3626**	0.0450	0.0334	0.0217	0.0072	0.0037
	<.0001	<.0001	<.0001	<.0001	<.0001	0.0020
1-2 Years Ago	0.0540	**0.3362**	0.0213	0.0192	0.0041	0.0064
	<.0001	<.0001	<.0001	<.0001	0.0006	<.0001
2-3 Years Ago	0.0388	0.0210	**0.3668**	0.0133	0.0106	0.0027
	<.0001	<.0001	<.0001	<.0001	<.0001	0.0232
3-4 Years Ago	0.0146	0.0214	0.0124	**0.3972**	-0.0009	-0.0016
	<.0001	<.0001	<.0001	<.0001	0.4745	0.1878
4-5 Years Ago	0.0010	-0.0013	0.0057	-0.0009	**0.4369**	-0.0014
	0.4128	0.2909	<.0001	0.4314	<.0001	0.2379
5+ Years Ago	0.0019	-0.0027	-0.0024	-0.0020	-0.0016	**0.3603**
	0.1207	0.0245	0.0478	0.0967	0.1761	<.0001

Note: Correlation coefficients are presented along with the p-values under the hypothesis that ρ=0. The restricted sample of 696,782 observations is used.

Collapsed Model

Table 1.6 first presents the estimated coefficients from the overall model after collapsing the yearly separation indicators into a single measure of whether a worker's history includes an exit induced by the firm or the individual.[25] Members of both affected groups have hourly wages and weekly hours that significantly differ from those of their employed counterparts who have not endured job separations, as seen in Figures 1.3 and 1.4. Reemployment subsequent to layoff increases weekly hours 4.1% above the hours of those with continuing employment in the full SIPP sample, whereas high attachment workers spend 3.1% more time on the job. This partially alleviates the economic burden of earning a wage that is diminished by 7.9% and 9.2% for these subsets, respectively. These actions contrast sharply with the behaviors of those who have been forced to separate from an employer because of a disabling condition. For recovering workers in the restricted sample, weekly hours are reduced 6.8% and the hourly wage rate is 21.3% less than that of the base population.

Worker behaviors subsequent to these exogenous occurrences are summarized by event type as follows: those with firm-induced job terminations in their past consistently work more hours at a lower hourly wage rate once with a new employer, whereas those who parted from their job because of reasons relating to personal disability work fewer hours while earning a wage rate that is by comparison even more negatively impacted. The full and highly attached samples of workers provide similar estimates of these shocks, and these patterns are reflected when using both the SIPP measures of a limiting health condition and those derived from SSA data

[25]This is equivalent to allowing the summation index, m, to only take on the value 1 in equations (1.1) and (1.2).

Table 1.6: Joint Estimation of Wage and Hours with Person and Job Heterogeneity- Single Indicator of Shock

	Unrestricted Sample		**Restricted Sample**			
	SIPP Health Measures		**SIPP Health Measures**		**SSA Health Measures**	
	Hourly Wage	**Weekly Hours**	**Hourly Wage**	**Weekly Hours**	**Hourly Wage**	**Weekly Hours**
Exogenous Shocks:						
Health Shock in Past	-0.2487 ***	-0.0833 ***	-0.2392 ***	-0.0700 ***	-0.2504 ***	-0.0759 ***
	(0.0100)	(0.0090)	(0.0117)	(0.0105)	(0.0176)	(0.0168)
Layoff Shock in Past	-0.0824 ***	0.0402 ***	-0.0950 ***	0.0313 ***	-0.0970 ***	0.0307 ***
	(0.0062)	(0.0061)	(0.0067)	(0.0065)	(0.0067)	(0.0065)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3175	0.1799	0.3140	0.1756	0.3140	0.1756
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3156	0.2221	0.3054	0.2021	0.3079	0.2025
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4977		0.4815		0.4840	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3586	0.4146	0.3506	0.4103	0.3507	0.4103
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2571		0.2608		0.2606	
Number of Workers	34,906		28,164		28,164	
Number of Jobs	62,507		50,833		50,833	
ln-L	-192,712.58		-131,181.42		-131,306.30	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

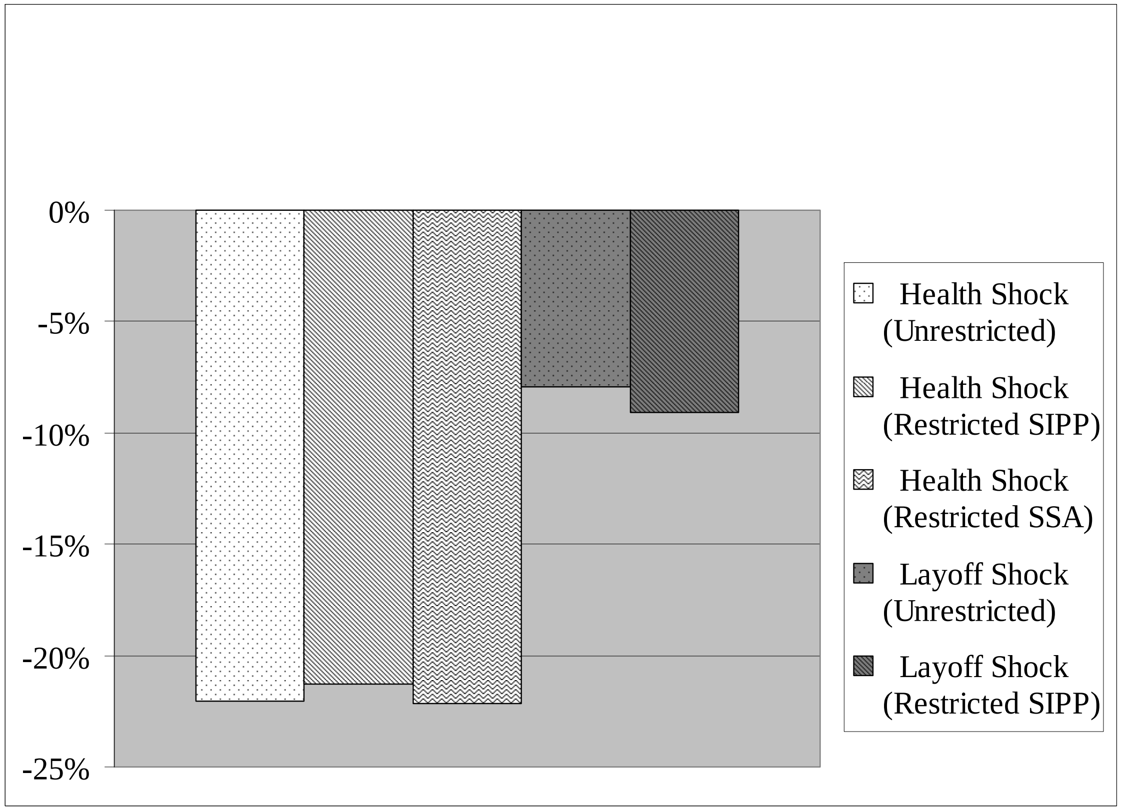

Figure 1.3: Percent Effect of Past Layoff or Health Shock on Hourly Wage Rate (Single Indicator)

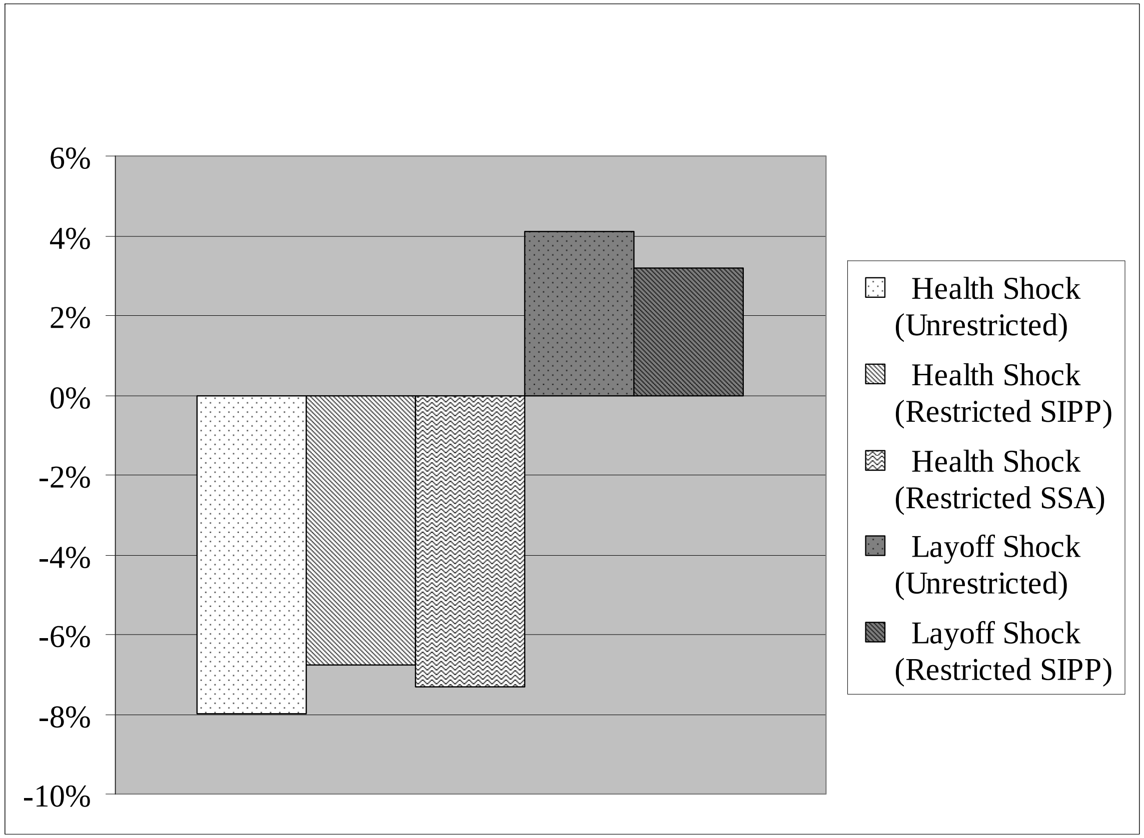

Figure 1.4: Percent Effect of Past Layoff or Health Shock on Weekly Hours (Single Indicator)

sources.

Expanded Model

I next introduce the full model described by equations (1.2) and (1.2), extending the model to include detailed information regarding the number of years that have elapsed since the date of the shock in order to more precisely compare the periods of adjustment following these separations. Table 1.10 presents the estimated coefficients from Tables 1.7, 1.8, and 1.9 as percent effects for ease of interpretation, while Figures 1.5 and 1.6 graphically depict the results.[26] Broad patterns emerge that are consistent with the results of the collapsed model in Table 1.6.

Those with layoffs in their past demonstrate increased hours at work regardless of the number of years that have passed since the date of the event.[27] Individuals in the unrestricted sample with a job history that includes a layoff spend approximately 2% more hours at work in the first two years back. This level of productivity improves to 5.6% more hours on the job after five years have passed since the displacement occurred. Those in the restricted sample who experienced this same event steadily increase their hours at work by around 0.5 percentage points over each of the next several years. In doing so, in five years they shift from working 1.2% to 3.9% more hours than those with continuous employment.

It may be the case that those who previously were laid off are attempting to exhibit a greater degree of productivity to their new employers in order to avoid

[26]The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: $e^{\delta} - 1$.

[27]Layoff estimates do not substantially differ when using SIPP and SSA variables in the restricted sample because these indicators remain constant across models. For this reason, only the results of the restricted SIPP sample will be compared to those from the full sample.

Table 1.7: Joint Estimation of Wage and Hours with Person and Job Heterogeneity for the Unrestricted Sample

	SIPP Health Measures	
	Hourly Wage	**Weekly Hours**
Own Exogenous Health Shock:		
0-1 Year Ago	-0.2334 ***	-0.0762 ***
	(0.0080)	(0.0057)
1-2 Years Ago	-0.1424 ***	-0.0596 ***
	(0.0082)	(0.0052)
2-3 Years Ago	-0.1208 ***	-0.0481 ***
	(0.0086)	(0.0056)
3-4 Years Ago	-0.1029 ***	-0.0362 ***
	(0.0098)	(0.0056)
4-5 Years Ago	-0.0866 ***	-0.0025
	(0.0123)	(0.0067)
5+ Years Ago	-0.0478 ***	0.0237 **
	(0.0134)	(0.0072)
Own Exogenous Layoff Shock:		
0-1 Year Ago	-0.0800 ***	0.0170 ***
	(0.0046)	(0.0030)
1-2 Years Ago	-0.0708 ***	0.0192 ***
	(0.0045)	(0.0028)
2-3 Years Ago	-0.0463 ***	0.0340 ***
	(0.0047)	(0.0029)
3-4 Years Ago	-0.0308 ***	0.0387 ***
	(0.0049)	(0.0029)
4-5 Years Ago	-0.0339 ***	0.0435 ***
	(0.0055)	(0.0031)
5+ Years Ago	-0.0067	0.0548 ***
	(0.0057)	(0.0033)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3175	0.1798
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3155	0.2225
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4997	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3587	0.4146
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2576	
Number of Workers	34,906	
Number of Jobs	62,507	
ln-L	-192,588.85	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.8: Joint Estimation of Wage and Hours with Person and Job Heterogeneity for the Restricted Sample

	SIPP Health Measures	
	Hourly Wage	**Weekly Hours**
Own Exogenous Health Shock:		
0-1 Year Ago	-0.2177 ***	-0.0580 ***
	(0.0095)	(0.0066)
1-2 Years Ago	-0.1248 ***	-0.0563 ***
	(0.0094)	(0.0059)
2-3 Years Ago	-0.1022 ***	-0.0292 ***
	(0.0095)	(0.0066)
3-4 Years Ago	-0.0982 ***	-0.0423 ***
	(0.0109)	(0.0066)
4-5 Years Ago	-0.1183 ***	-0.0278 **
	(0.0138)	(0.0086)
5+ Years Ago	-0.0660 ***	-0.0041
	(0.0160)	(0.0093)
Own Exogenous Layoff Shock:		
0-1 Year Ago	-0.0861 ***	0.0120 ***
	(0.0049)	(0.0030)
1-2 Years Ago	-0.0788 ***	0.0143 ***
	(0.0047)	(0.0028)
2-3 Years Ago	-0.0587 ***	0.0260 ***
	(0.0049)	(0.0028)
3-4 Years Ago	-0.0404 ***	0.0326 ***
	(0.0051)	(0.0029)
4-5 Years Ago	-0.0402 ***	0.0349 ***
	(0.0058)	(0.0031)
5+ Years Ago	-0.0158 **	0.0385 ***
	(0.0060)	(0.0033)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3140	0.1756
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3053	0.2025
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4836	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3507	0.4103
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2611	
Number of Workers	28,164	
Number of Jobs	50,833	
ln-L	-131,119.91	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.9: Joint Estimation of Wage and Hours with Person and Job Heterogeneity for the Restricted Sample

	SSA Health Measures	
	Hourly Wage	**Weekly Hours**
Own Exogenous Health Shock:		
0-1 Year Ago	-0.2428 ***	-0.0766 ***
	(0.0169)	(0.0105)
1-2 Years Ago	-0.1484 ***	-0.0874 ***
	(0.0166)	(0.0081)
2-3 Years Ago	-0.1784 ***	-0.0472 **
	(0.0170)	(0.0169)
3-4 Years Ago	-0.1380 ***	-0.0983 ***
	(0.0199)	(0.0171)
4-5 Years Ago	-0.2372 ***	-0.0731 ***
	(0.0258)	(0.0200)
5+ Years Ago	-0.0864 *	-0.0432
	(0.0402)	(0.0229)
Own Exogenous Layoff Shock:		
0-1 Year Ago	-0.0890 ***	0.0116 ***
	(0.0049)	(0.0029)
1-2 Years Ago	-0.0813 ***	0.0139 ***
	(0.0047)	(0.0028)
2-3 Years Ago	-0.0609 ***	0.0256 ***
	(0.0049)	(0.0028)
3-4 Years Ago	-0.0423 ***	0.0321 ***
	(0.0051)	(0.0028)
4-5 Years Ago	-0.0418 ***	0.0345 ***
	(0.0058)	(0.0031)
5+ Years Ago	-0.0172 **	0.0381 ***
	(0.0060)	(0.0032)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3140	0.1756
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3076	0.2028
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4861	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3508	0.4102
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2609	
Number of Workers	28,164	
Number of Jobs	50,833	
ln-L	-131,224.56	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.10: Percent Effect of Exogenous Health and Layoff Shocks on Hourly Wage and Weekly Hours- Significant Values Only

	Unrestricted Sample		**Restricted Sample**			
	SIPP Health Measures		**SIPP Health Measures**		**SSA Health Measures**	
	Hourly Wage	**Weekly Hours**	**Hourly Wage**	**Weekly Hours**	**Hourly Wage**	**Weekly Hours**
Own Exogenous Health Shock:						
0-1 Year Ago	-0.2082	-0.0734	-0.1956	-0.0564	-0.2156	-0.0737
1-2 Years Ago	-0.1327	-0.0579	-0.1173	-0.0547	-0.1379	-0.0837
2-3 Years Ago	-0.1138	-0.0470	-0.0972	-0.0288	-0.1634	-0.0461
3-4 Years Ago	-0.0978	-0.0356	-0.0935	-0.0414	-0.1289	-0.0936
4-5 Years Ago	-0.0830	-	-0.1116	-0.0274	-0.2112	-0.0705
5+ Years Ago	-0.0467	0.0240	-0.0639	-	-0.0828	-
Own Exogenous Layoff Shock:						
0-1 Year Ago	-0.0769	0.0171	-0.0825	0.0121	-0.0852	0.0117
1-2 Years Ago	-0.0684	0.0194	-0.0758	0.0144	-0.0781	0.0140
2-3 Years Ago	-0.0452	0.0346	-0.0570	0.0263	-0.0591	0.0259
3-4 Years Ago	-0.0303	0.0395	-0.0396	0.0331	-0.0414	0.0326
4-5 Years Ago	-0.0333	0.0445	-0.0394	0.0355	-0.0409	0.0351
5+ Years Ago	-	0.0563	-0.0157	0.0393	-0.0171	0.0388

Note: The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: e^{δ}-1.

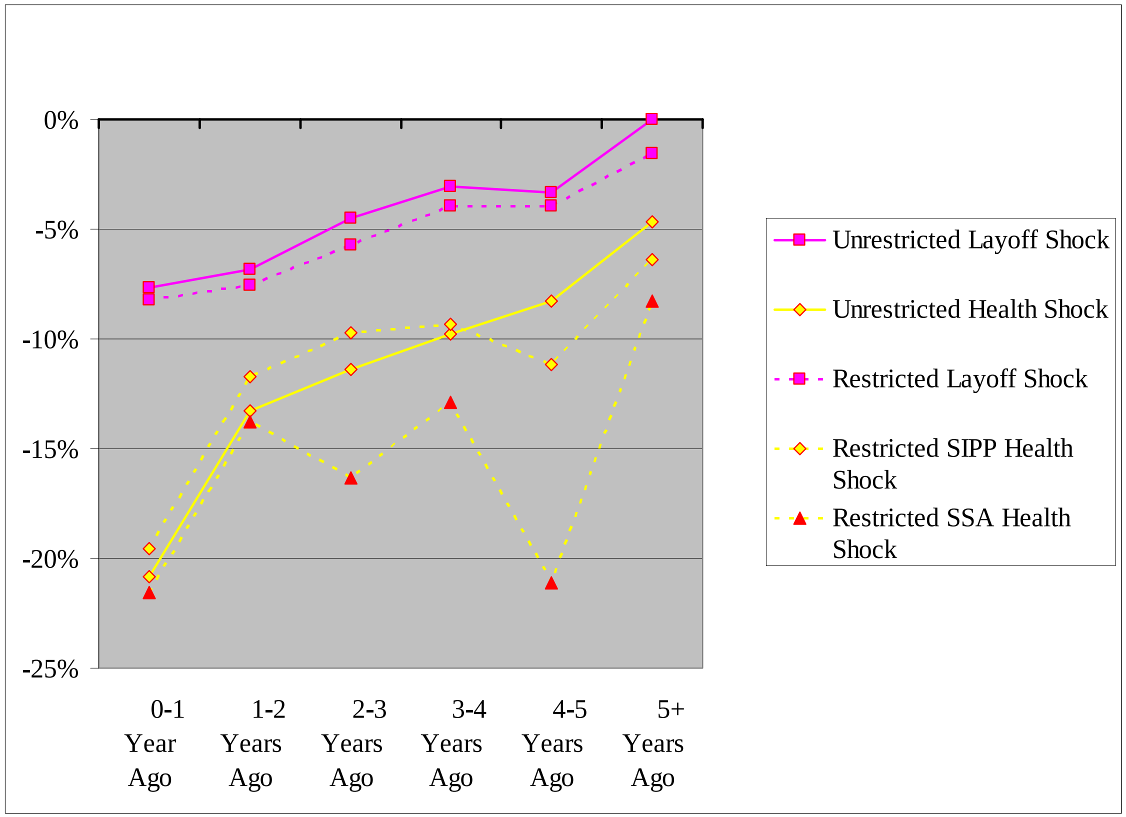

Figure 1.5: Percent Effect of Exogenous Layoff and Health Shocks on Hourly Wage Rate

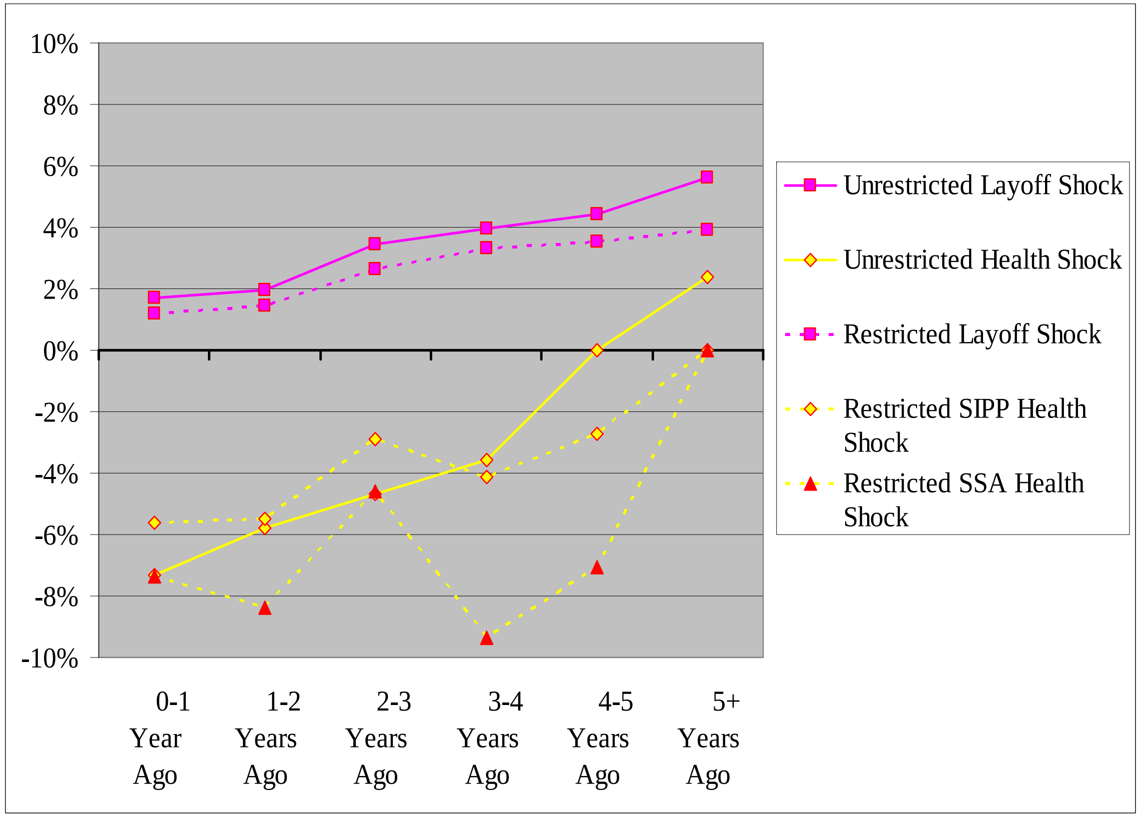

Figure 1.6: Percent Effect of Exogenous Layoff and Health Shocks on Weekly Hours

being the marginal workers chosen by the firm should a reduction of its work force become necessary. However, upon reviewing the coefficient estimates of the wage equation it becomes apparent that this is not the sole possible explanation for this behavior. These employees may also be adjusting the length of their work weeks because their hourly wage rates in the first year since the displacement are only 92% of their values as compared to before they were laid off. As time progresses beyond the actual year of separation, the wage rates for this category of workers improve by around 1 to 2 percentage points each year so that those with the oldest shocks are also those who are the least negatively impacted.

The unrestricted and restricted samples exhibit the same post-layoff trends, but those in the high attachment sample have hourly wage rates that are roughly 1 percentage point less each year than those in the unrestricted sample. One explanation for this is that workers who comprise the sample eligible to apply for SSDI may have a stronger desire to form more immediate job attachments when a job relationship is severed. Instead of considering as many competing wage offers as those in the unrestricted sample, these individuals may have chosen to accept a lower hourly wage rate rather than remain among the unemployed. On the other hand, it may be that new employment has been found in a new occupation or industry, and the loss of specific human capital is revealed through the dampened wages. The degree of impact observed in the coefficients of Tables 1.7-1.9 is less severe than the findings of Stevens (1997), in particular beyond the first year, and my estimates reveal a more rapid decline in the persistence of the shocks.

Those who have reestablished themselves in the workplace after a spell of failing health similarly experience lingering detrimental effects from their time out of the work force. However, in addition to having diminished wage rates, the fact that the shock was internal also reduces the hours of these individuals. Within the first year of the exogenous health event for the unrestricted sample, weekly hours fall by 7.3%. This impact is -5.6% when utilizing survey measures in the limited sample in that same time frame. The impact on hours only appears to truly begin to diminish in the fourth year since the date of the health setback for those in the subset of highly attached workers, while the complete sample demonstrates monotone improvements throughout. After more than five years since the onset of the impairment, the full sample indicates that those with latent health problems begin to compensate for their losses by working 2.4% more than the control population of workers. The limited sample does not recover as readily, but after five years have passed, this group appears to be indistinguishable from those with continuous employment in terms of the amount of time spent at work.

Monetary losses that are associated with reentry into the work force subsequent to a disabling incident are substantial. A worker in the unrestricted sample who is back at work within one year of an illness has a wage rate that is 79.2% of its former value. After an additional year of recovery, this improves to 86.7%, and after five years more have passed, wages are only 4.7% below the rates of those who have not experienced such dislocations. For the restricted group, the most severe impact to wages is similarly found for those back at work within the first year. These individuals earn 80.4% of their predisplacement hourly wages when using the SIPP health measures. After a second year passes, the losses associated with these rates have been nearly halved to -11.7%. Thereafter, the survey health indicators show that the wage rate for the restricted group remains around 90%. After five years, wages are 93.6% of their values as compared to before they experienced a health shock.

For each specification, effects are more severe for those with a past health ailment than they are for those who have been laid off. In contrast with those who have returned to work following a layoff, the effects on those who have previously endured an illness remain substantial even after five years or more have passed. Being highly attached to the work force seems to be to the benefit of those with impairments within four years of the date of the onset of disability.

Of the health measures used, SSA indicators reveal the most negative consequences for those with a job separation induced by disability. Estimates reveal less presence at work than those derived from survey measures: by comparison within the first three years, weekly hours are 2 to 3 percentage points lower for rejected SSDI applicants. Thereafter, weekly hours dramatically plummet to -9.4% as compared to -4.1% using SIPP indicators. The wage rates of reemployed SSDI applicants are consistently less than those who claim to have work limiting conditions. Three years after the onset of a disability, their wage losses fall to 83.7% of their base value before improving to 87.1% in the following year. After five years, wages remain depressed by 8.3%.

The group of highly attached workers have wage rates that are differentially impacted as compared to the full sample within the first few years after the displacing event depending on the impetus for the exit: being fully and disability insured lessens the negative effects of poor health, whereas it seemingly worsens those of layoff. Using administrative measures, penalties from ill health are found to be significant and lasting, with greatly depressed wage rates and weekly hours. These behaviors, combined as they are, greatly amplify earnings losses for this class of workers. It is interesting to note that the survey variables do appear to follow the same trends but do not capture the severity of the traumas because the results incorporate those with more mild impairments.

Simulated Earnings Losses

To quantify the impact of these setbacks, I consider the plight of a newly reemployed worker who experienced her first employment shock in the previous year and who does not suffer from any additional separations in the next six years. Using the restricted sample as a base for this comparison, I know from the summary statistics in Table 1.1 that the average employed individual in the restricted sample earned a wage rate of $15.26 and worked 38.89 weekly hours, resulting in a yearly salary of $30,860.[28] For each type of shock, Table 1.11 simulates the estimated yearly salaries of workers who experience a layoff or ill health event that forces them to part from their jobs. Along with these values are the calculated differences from the average earnings of an otherwise identical worker who has not endured any exogenous shocks.[29]

Figure 1.7 demonstrates that in the case of a layoff, the simulated worker earns $2,204 less in the year immediately following the displacing event, but is able to regain some of her losses through improvements to her hourly wage and weekly hours over the next several years. By the completion of her sixth year back, her yearly salary is $709 more than it would have been without the separation. Cumulatively over this period, she is $4,819 less wealthy.

If this were a health setback instead, the worker would find herself in an even more disadvantaged economic situation. Either health measure indicates that the disparity in annual earnings is still larger in magnitude for those who experienced

[28]Annual salaries are based upon 52 weeks of employment.

[29]Actual earnings losses within the first year following a displacing event are conservative in Table 1.11 because they do not allow for gaps between jobs during the transitioning period.

Table 1.11: Simulation of Earnings upon Reentry into the Workforce Following an Exogenous Separation

Own Exogenous Shock- Layoff

Year	Hourly Wage	Weekly Hours	Yearly Salary	Difference
1	$14.00	39.36	$28,656	-$2,204
2	$14.10	39.45	$28,932	-$1,928
3	$14.39	39.91	$29,867	-$993
4	$14.66	40.18	$30,620	-$240
5	$14.66	40.27	$30,697	-$163
6	$15.02	40.42	$31,569	$709
Total				-$4,819

Own Exogenous Shock- SIPP Health Measures

Year	Hourly Wage	Weekly Hours	Yearly Salary	Difference
1	$12.27	36.70	$23,424	-$7,436
2	$13.47	36.76	$25,748	-$5,112
3	$13.78	37.77	$27,060	-$3,800
4	$13.83	37.28	$26,815	-$4,045
5	$13.56	37.82	$26,665	-$4,195
6	$14.29	38.89	$28,889	-$1,971
Total				-$26,559

Own Exogenous Shock- SSA Health Measures

Year	Hourly Wage	Weekly Hours	Yearly Salary	Difference
1	$11.97	36.02	$22,422	-$8,438
2	$13.16	35.64	$24,378	-$6,482
3	$12.77	37.10	$24,627	-$6,233
4	$13.29	35.25	$24,365	-$6,495
5	$12.04	36.15	$22,627	-$8,233
6	$14.00	38.89	$28,306	-$2,554
Total				-$38,434

Note: Values are compared with the averages for the restricted sample: an hourly wage of $15.26 and weekly hours of 38.89, which result in a yearly salary of $30,860.

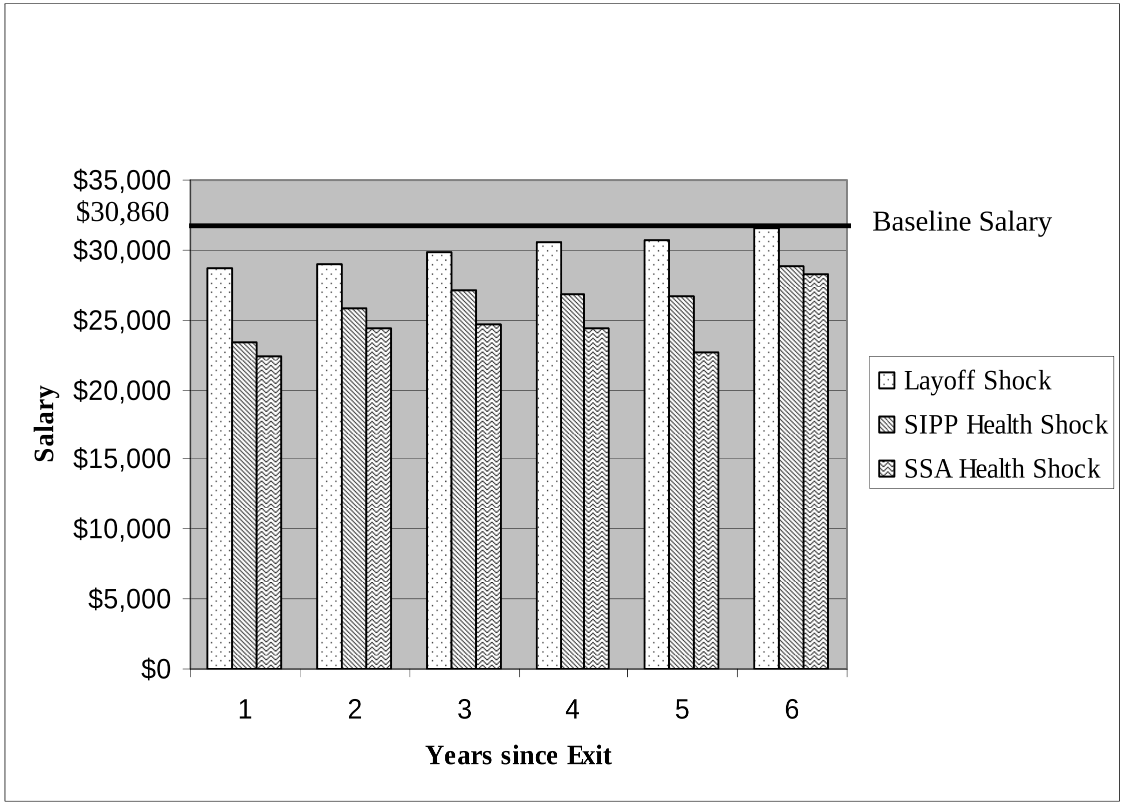

Figure 1.7: Simulation of Earnings upon Reentry into the Workforce Following Displacement

poor health six years ago than after only just the first year following a layoff. Furthermore, the total decrease in earnings over all six years for a layoff is still less than just the first-year losses immediately after recovery from an illness.

Using SIPP and SSA health measures, $7,436 and $8,438 are the respective losses in the initial year which dwindle to $1,971 and $2,554 after completion of the sixth year. The lasting impact of disabling conditions is significant and severe, with salaries remaining just above $4,000 in the third through fifth years following reentry into the workplace using SIPP-based measures and earnings losses decreasing to $6,233 in the third year but spiking to $8,233 in the fifth when utilizing SSA measures. In all, disability that induces an employee-employer separation results in damages of $26,559 or $38,434 to a worker's cumulative income following six years of uninterrupted work depending on whether demographic or administrative records are the basis for the information regarding the health shock.

Demographic Characteristics

Broad categories of education, gender, and race seemingly have important roles in the plight of the displaced as they reenter the work force. A paper by Stevens (1997) remarks upon the significance of the role of education in wage reductions following layoff. She finds that those with graduate schooling are better able to manage the associated losses than are people who have enrolled in some post-secondary education. Kletzer and Fairlie (2003) have independently explored the wage rates and hours of men and women after this type of event, confirming that adjustment behaviors also vary by gender. Analyzing a population of workers dislocated from high-technology positions, a case study by Ong (1991) uncovers that the post-displacement earnings of blacks and Hispanics are more severely hit by abrupt job terminations than are the salaries of whites. I reexamine these findings and extend them below to include the analogous displacing health shocks.

Education Considering the lasting impacts of employee-employer separation by two education groups enables an examination of the manner in which the level of schooling affects future labor outcomes. Tables 1.12 and 1.13 present the estimated coefficients, while Table 1.14 presents the percent effects from the joint model that interacts the occurrences of job separation with two education groups: those with a high school degree or less and those with more than a high school degree. This partition enables an exploration of the theory that the recovery periods following job separations may differ by education.

Those with more than a high school diploma who have been laid off exhibit behaviors that differ from those of their counterparts who are less educated in two noteworthy manners. The first of these is that their hourly wages are harder hit, but only moderately so, as seen in Figure 1.8. This agrees with Stevens (1997), who finds that groups with 13-15 years of schooling have greater monetary losses than those with only a high school diploma who have returned to work following a layoff. The second is that upon reestablishing themselves at a new place of employment, those with more schooling immediately begin exerting more observable effort on the job. Figure 1.9 exhibits the manner in which employees with more than a high school education who suffered a layoff spend a between 3.3% and 5.3% more weekly hours on the job each year they are back, whereas those with less schooling do not significantly alter their behavior in the first few years following a layoff. Only after four years have passed do less educated workers begin to work 1.8% more hours. After five years, this has risen to 3.5%, which is comparable to the level of exertion

Table 1.12: Joint Estimation of Wage and Hours by Education Level for the Restricted Sample (SIPP Health Measures)

	Restricted SIPP Health Measures			
	Hourly Wage		Weekly Hours	
	≤ HS	**HS +**	**≤ HS**	**HS +**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.1953 ***	-0.2490 ***	-0.0561 ***	-0.0567 ***
	(0.0144)	(0.0137)	(0.0092)	(0.0099)
1-2 Years Ago	-0.1010 ***	-0.1621 ***	-0.0744 ***	-0.0366 ***
	(0.0137)	(0.0142)	(0.0079)	(0.0090)
2-3 Years Ago	-0.0464 ***	-0.1749 ***	-0.0404 ***	-0.0172
	(0.0136)	(0.0144)	(0.0093)	(0.0098)
3-4 Years Ago	-0.0685 ***	-0.1376 ***	-0.0754 ***	-0.0035
	(0.0154)	(0.0167)	(0.0093)	(0.0099)
4-5 Years Ago	-0.0858 ***	-0.1608 ***	-0.0334 **	-0.0281 *
	(0.0194)	(0.0215)	(0.0122)	(0.0136)
5+ Years Ago	-0.0556 **	-0.0813 **	0.0060	-0.0256
	(0.0211)	(0.0300)	(0.0125)	(0.0157)
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0793 ***	-0.0934 ***	-0.0073	0.0365 ***
	(0.0067)	(0.0072)	(0.0049)	(0.0039)
1-2 Years Ago	-0.0705 ***	-0.0878 ***	0.0011	0.0322 ***
	(0.0065)	(0.0071)	(0.0047)	(0.0037)
2-3 Years Ago	-0.0565 ***	-0.0604 ***	0.0063	0.0519 ***
	(0.0068)	(0.0072)	(0.0048)	(0.0037)
3-4 Years Ago	-0.0399 ***	-0.0398 ***	0.0178 ***	0.0518 ***
	(0.0071)	(0.0076)	(0.0050)	(0.0037)
4-5 Years Ago	-0.0320 ***	-0.0502 ***	0.0270 ***	0.0447 ***
	(0.0082)	(0.0082)	(0.0053)	(0.0041)
5+ Years Ago	-0.0089	-0.0241 **	0.0348 ***	0.0412 ***
	(0.0084)	(0.0087)	(0.0057)	(0.0041)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3140		0.1756	
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3052		0.2021	
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4853			
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3508		0.4103	
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2609			
Number of Workers	28,164			
Number of Jobs	50,833			
ln-L	-131,051.88			

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.13: Joint Estimation of Wage and Hours by Education Level for the Restricted Sample (SSA Health Measures)

	Restricted SSA Health Measures			
	Hourly Wage		Weekly Hours	
	$\leq$ HS	**HS +**	**$\leq$ HS**	**HS +**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2455 ***	-0.2243 ***	-0.0841 ***	-0.0755 ***
	(0.0217)	(0.0328)	(0.0134)	(0.0218)
1-2 Years Ago	-0.1138 ***	-0.1951 ***	-0.1995 ***	0.0353 *
	(0.0235)	(0.0278)	(0.0115)	(0.0138)
2-3 Years Ago	-0.0303	-0.3191 ***	-0.0961 ***	0.0105
	(0.0379)	(0.0288)	(0.0225)	(0.0363)
3-4 Years Ago	-0.1616 ***	-0.1797 ***	-0.1536 **	-0.0437
	(0.0346)	(0.0392)	(0.0532)	(0.0316)
4-5 Years Ago	-0.2822 ***	-0.2588 ***	-0.0676	-0.0719
	(0.0480)	(0.0395)	(0.0559)	(0.0392)
5+ Years Ago	-0.0643	-0.1583	-0.0352	-0.0495
	(0.0670)	(0.0925)	(0.0534)	(0.0410)
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0818 ***	-0.0973 ***	-0.0076	0.0361 ***
	(0.0068)	(0.0071)	(0.0049)	(0.0039)
1-2 Years Ago	-0.0730 ***	-0.0911 ***	0.0006	0.0320 ***
	(0.0065)	(0.0070)	(0.0047)	(0.0037)
2-3 Years Ago	-0.0585 ***	-0.0637 ***	0.0057	0.0518 ***
	(0.0068)	(0.0072)	(0.0048)	(0.0037)
3-4 Years Ago	-0.0419 ***	-0.0426 ***	0.0175 ***	0.0514 ***
	(0.0072)	(0.0076)	(0.0050)	(0.0036)
4-5 Years Ago	-0.0335 ***	-0.0527 ***	0.0266 ***	0.0443 ***
	(0.0082)	(0.0082)	(0.0053)	(0.0040)
5+ Years Ago	-0.0101	-0.0265 **	0.0344 ***	0.0408 ***
	(0.0084)	(0.0087)	(0.0057)	(0.0040)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3139		0.1756	
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3074		0.2025	
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4874			
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3508		0.4103	
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2608			
Number of Workers	28,164			
Number of Jobs	50,833			
ln-L	-131,125.37			

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.14: Percent Effect of Exogenous Health and Layoff Shocks on Hourly Wage and Weekly Hours by Education Level- Significant Values Only

	Restricted SIPP Health Measures			
	Hourly Wage		**Weekly Hours**	
	$\leq$ HS	**HS +**	**$\leq$ HS**	**HS +**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.1774	-0.2204	-0.0546	-0.0551
1-2 Years Ago	-0.0961	-0.1496	-0.0717	-0.0359
2-3 Years Ago	-0.0453	-0.1605	-0.0396	-
3-4 Years Ago	-0.0662	-0.1286	-0.0726	-
4-5 Years Ago	-0.0822	-0.1485	-0.0328	-0.0277
5+ Years Ago	-0.0541	-0.0781	-	-
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0762	-0.0892	-	0.0372
1-2 Years Ago	-0.0681	-0.0841	-	0.0327
2-3 Years Ago	-0.0549	-0.0586	-	0.0533
3-4 Years Ago	-0.0391	-0.0390	0.0180	0.0532
4-5 Years Ago	-0.0315	-0.0490	0.0274	0.0457
5+ Years Ago	-	-0.0238	0.0354	0.0421

	Restricted SSA Health Measures			
	Hourly Wage		**Weekly Hours**	
	$\leq$ HS	**HS +**	**$\leq$ HS**	**HS +**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2177	-0.2009	-0.0807	-0.0727
1-2 Years Ago	-0.1076	-0.1772	-0.1809	0.0359
2-3 Years Ago	-	-0.2732	-0.0916	-
3-4 Years Ago	-0.1492	-0.1645	-0.1424	-
4-5 Years Ago	-0.2459	-0.2280	-	-
5+ Years Ago	-	-	-	-
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0785	-0.0927	-	0.0368
1-2 Years Ago	-0.0704	-0.0871	-	0.0325
2-3 Years Ago	-0.0568	-0.0617	-	0.0532
3-4 Years Ago	-0.0410	-0.0417	0.0177	0.0527
4-5 Years Ago	-0.0329	-0.0513	0.0270	0.0453
5+ Years Ago	-	-0.0262	0.0350	0.0416

Note: The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: e^{δ}-1.

of the more highly educated.

During the first couple of years back at work, those with disabling conditions and advanced schooling begin to make up for some of their economic losses by improving their weekly hours at work. They are able to do so more rapidly than those with less education. During the third year after the episode of poor health that led to the termination of their job, workers with at most a secondary education in the restricted SIPP-based sample work 92.7% of their predisplacement weekly hours, while SSA measures indicate this is 85.8%. For the better educated, the estimated coefficients do not significantly differ from zero which implies that these workers are have not adjusted their hours from what they would have been absent an illness.

Contrasting with the observed patterns of behavior manifested in the weekly hours of reemployed individuals, the less educated are the ones who are better able to mitigate wage losses over time. For neither education group is this a steady improvement. In fact, after four years the wage rates are again hovering around their values from one year after the date of the displacement: 91.8% and 85.2% for those with less and more education, respectively, according to SIPP indicators. The model that utilizes the administrative measures of impairment-related separations provides the grimmest interpretation of how these workers fare following an exogenous shock, as no indications of relief are apparent. As an example of this, three years after the date of dislocation wage losses for those with at least a secondary school education are 14.9% as compared to the rates of those with continuous employment. One year later, monetary losses have fallen to 24.6% for this category of workers. The survey data depict more mild transitions over this period, with the less educated experiencing reductions in their wage rates of

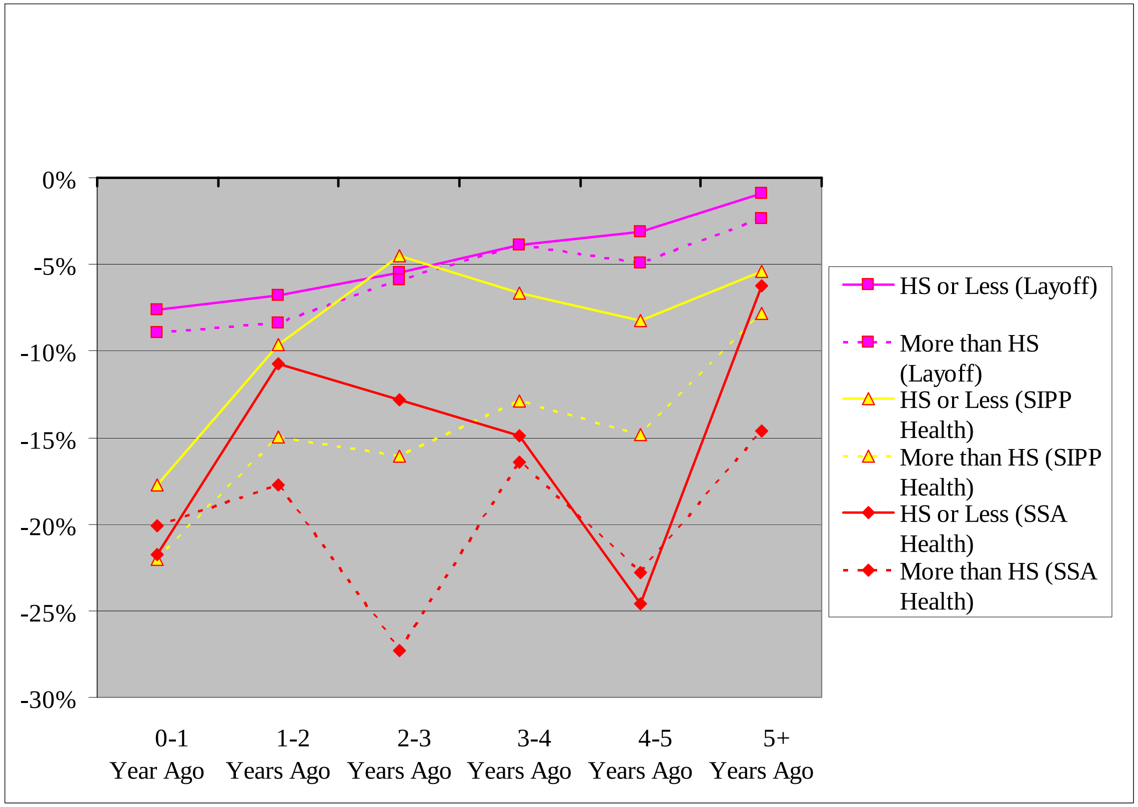

Figure 1.8: Percent Effect of Exogenous Layoff and Health Shocks on Hourly Wage Rate by Educational Attainment

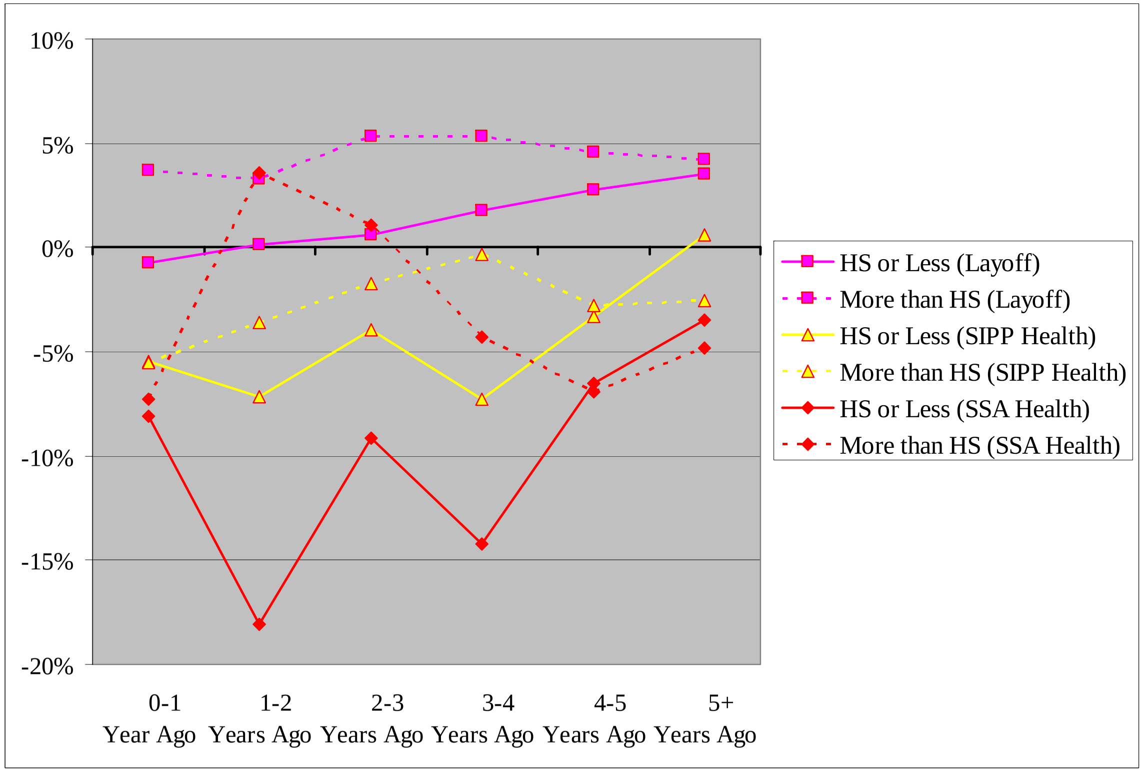

Figure 1.9: Percent Effect of Exogenous Layoff and Health Shocks on Weekly Hours by Educational Attainment

1.6 percentage points in that time span.

The level of schooling plays an important role in determining the severity of the lasting effects of job dislocations. Most notably, survey measures show that those with more education who return to work following an unanticipated exit almost consistently earn a lower wage rate regardless of whether the source of the forced separation was a layoff or disability. [30] Those with at most a high school degree, however, do not spend as many hours at work as do those who enrolled in advanced courses. For the health separations, this behavior may be associated with the fact that those with more schooling may be less inclined to have jobs that are physically taxing. A health event that forces a worker with a higher level of aptitude to part with her employer may be a larger disturbance, and the more greatly reduced wage rates may be indicative of these workers establishing new job matches that are less demanding. Additionally, better educated workers may generally have more specific human capital that is less transferable across positions.

The disparity in wages by education is most apparent within the collection of workers who have experienced an episode of ill health, particularly when referencing results that incorporate SIPP measures. As time passes since the date of the health shock, those with a high school diploma or less exhibit more marked signs of recovery from these monetary losses, particularly when referencing the results of SIPP indicators. This gap is less apparent in the restricted SSA-based sample, which may be indicative of more equivalent knowledge of impairments across these groups (Currie and Madrian 1999).

[30] In the year of the displacement, those with less education have wages that are 78.2% of their potential rate, whereas those the more highly educated earn 79.9% of this value. This pattern is again reflected in the fourth year since the job separation.

Gender Following a layoff, Tables 1.15, 1.16, and 1.17 indicate that employed females work more each week than males with a similar history. Men do not significantly alter their hours until a few years have passed since the layoff. The amount of increased exertion for men is 3.5% five years or more after the shock, which is consistent with Kletzer and Fairlie (2003). The percent of increased weekly hours for women when referencing the results for the complete sample increases from 4% to 7.9% above the hours nondisplaced employees by the end of the third year before tapering off to 5.9% four years following a layoff.

It is curious that women spend more time than do their male counterparts at work subsequent to a layoff given that post-layoff wage rates for men and women are not dissimilarly impacted, as illustrated by Figure 1.10. In nearly each of the first three years, females appear to earn only marginally less than do male workers with this type of job interruption. Within a year of the layoff event, men have wage rates that are 92.2% of predisplacement rates, while women earn 91.2%. Three years after they were laid off, women have regained some ground as compared to men, as both have wage rates that are only 3.9% less. My findings for men agree with Kletzer and Fairlie (2003) until around the third year of displacement when my SIPP sample exhibits greater recovery.

In considering forced health exits, it seems that women are not as affected by this type of event as are their male counterparts. Figure 1.11 shows that weekly hours in the first four years after an incidence of dislocation induced by ill health steadily improve from 93% to 98.2% for women. SIPP measures of health ailments show that weekly hours decrease from 93.2% to 92.7% over this same period for men, while women experience improvements from 95.4% to hours that do not significantly differ from those of workers who have not been forced to part with a

Table 1.15: Joint Estimation of Wage and Hours by Gender for the Restricted Sample (SIPP Health Measures)

	Restricted SIPP Health Measures			
	Hourly Wage		Weekly Hours	
	Men	**Women**	**Men**	**Women**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2521 ***	-0.1867 ***	-0.0701 ***	-0.0473 ***
	(0.0133)	(0.0142)	(0.0092)	(0.0099)
1-2 Years Ago	-0.1532 ***	-0.1005 ***	-0.0730 ***	-0.0425 ***
	(0.0146)	(0.0131)	(0.0083)	(0.0087)
2-3 Years Ago	-0.1597 ***	-0.0489 ***	-0.0754 ***	0.0120
	(0.0139)	(0.0136)	(0.0093)	(0.0100)
3-4 Years Ago	-0.0935 ***	-0.0901 ***	-0.0781 ***	-0.0110
	(0.0160)	(0.0158)	(0.0096)	(0.0097)
4-5 Years Ago	-0.1142 ***	-0.1089 ***	-0.0774 ***	0.0093
	(0.0237)	(0.0184)	(0.0151)	(0.0118)
5+ Years Ago	-0.1167 ***	-0.0306	-0.0451 *	0.0296 *
	(0.0332)	(0.0204)	(0.0191)	(0.0123)
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0810 ***	-0.0918 ***	-0.0010	0.0398 ***
	(0.0058)	(0.0091)	(0.0036)	(0.0065)
1-2 Years Ago	-0.0773 ***	-0.0794 ***	-0.0026	0.0497 ***
	(0.0055)	(0.0092)	(0.0033)	(0.0064)
2-3 Years Ago	-0.0525 ***	-0.0666 ***	0.0063	0.0663 ***
	(0.0057)	(0.0094)	(0.0033)	(0.0065)
3-4 Years Ago	-0.0398 ***	-0.0396 ***	0.0112 ***	0.0761 ***
	(0.0061)	(0.0097)	(0.0033)	(0.0066)
4-5 Years Ago	-0.0566 ***	-0.0141	0.0273 ***	0.0571 ***
	(0.0071)	(0.0103)	(0.0038)	(0.0068)
5+ Years Ago	-0.0374 ***	0.0189	0.0343 ***	0.0547 ***
	(0.0073)	(0.0106)	(0.0039)	(0.0070)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3139		0.1756	
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3054		0.2021	
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4844			
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3507		0.4103	
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2608			
Number of Workers	28,164			
Number of Jobs	50,833			
ln-L	-131,025.70			

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.16: Joint Estimation of Wage and Hours by Gender for the Restricted Sample (SSA Health Measures)

	Restricted SSA Health Measures			
	Hourly Wage		Weekly Hours	
	Men	**Women**	**Men**	**Women**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2734 ***	-0.2364 ***	-0.0974 ***	-0.0508 *
	(0.0217)	(0.0300)	(0.0149)	(0.0230)
1-2 Years Ago	-0.2147 ***	-0.0802 **	-0.0977 ***	-0.0939 ***
	(0.0238)	(0.0294)	(0.0123)	(0.0125)
2-3 Years Ago	-0.3013 ***	-0.0267	-0.0550 *	-0.0542
	(0.0217)	(0.0411)	(0.0229)	(0.0309)
3-4 Years Ago	-0.1417 ***	-0.1475 ***	-0.1304 ***	-0.0574
	(0.0366)	(0.0433)	(0.0232)	(0.0489)
4-5 Years Ago	-0.3203 ***	-0.2125 ***	-0.1507 **	-0.0125
	(0.0586)	(0.0451)	(0.0469)	(0.0510)
5+ Years Ago	-0.1487	-0.0678	-0.1251 **	0.0185
	(0.0850)	(0.0590)	(0.0393)	(0.0502)
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0861 ***	-0.0921 ***	-0.0018	0.0396 ***
	(0.0058)	(0.0091)	(0.0035)	(0.0065)
1-2 Years Ago	-0.0816 ***	-0.0796 ***	-0.0034	0.0498 ***
	(0.0055)	(0.0092)	(0.0032)	(0.0065)
2-3 Years Ago	-0.0565 ***	-0.0667 ***	0.0055	0.0663 ***
	(0.0057)	(0.0093)	(0.0033)	(0.0065)
3-4 Years Ago	-0.0432 ***	-0.0397 ***	0.0104 **	0.0761 ***
	(0.0061)	(0.0097)	(0.0033)	(0.0066)
4-5 Years Ago	-0.0596 ***	-0.0139	0.0264 ***	0.0571 ***
	(0.0071)	(0.0103)	(0.0038)	(0.0068)
5+ Years Ago	-0.0401 ***	0.0190	0.0335 ***	0.0547 ***
	(0.0073)	(0.0106)	(0.0038)	(0.0070)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3139		0.1756	
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3077		0.2025	
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4867			
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3507		0.4103	
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2607			
Number of Workers	28,164			
Number of Jobs	50,833			
ln-L	-131,140.82			

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.17: Percent Effect of Exogenous Health and Layoff Shocks on Hourly Wage and Weekly Hours by Gender- Significant Values Only

	Restricted SIPP Health Measures			
	Hourly Wage		**Weekly Hours**	
	Men	**Women**	**Men**	**Women**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2228	-0.1703	-0.0677	-0.0462
1-2 Years Ago	-0.1420	-0.0956	-0.0704	-0.0416
2-3 Years Ago	-0.1476	-0.0477	-0.0726	-
3-4 Years Ago	-0.0893	-0.0862	-0.0751	-
4-5 Years Ago	-0.1079	-0.1032	-0.0745	-
5+ Years Ago	-0.1101	-	-0.0441	0.0300
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0778	-0.0877	-	0.0406
1-2 Years Ago	-0.0744	-0.0763	-	0.0510
2-3 Years Ago	-0.0511	-0.0644	-	0.0685
3-4 Years Ago	-0.0390	-0.0388	0.0113	0.0791
4-5 Years Ago	-0.0550	-	0.0277	0.0588
5+ Years Ago	-0.0367	-	0.0349	0.0562

	Restricted SSA Health Measures			
	Hourly Wage		**Weekly Hours**	
	Men	**Women**	**Men**	**Women**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2392	-0.2105	-0.0928	-0.0495
1-2 Years Ago	-0.1932	-0.0771	-0.0931	-0.0896
2-3 Years Ago	-0.2601	-	-0.0535	-
3-4 Years Ago	-0.1321	-0.1371	-0.1223	-
4-5 Years Ago	-0.2741	-0.1914	-0.1399	-
5+ Years Ago	-	-	-0.1176	-
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0825	-0.0880	-	0.0404
1-2 Years Ago	-0.0784	-0.0765	-	0.0511
2-3 Years Ago	-0.0549	-0.0645	-	0.0685
3-4 Years Ago	-0.0423	-0.0389	0.0105	0.0791
4-5 Years Ago	-0.0579	-	0.0268	0.0588
5+ Years Ago	-0.0393	-	0.0341	0.0562

Note: The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: e^{δ}-1.

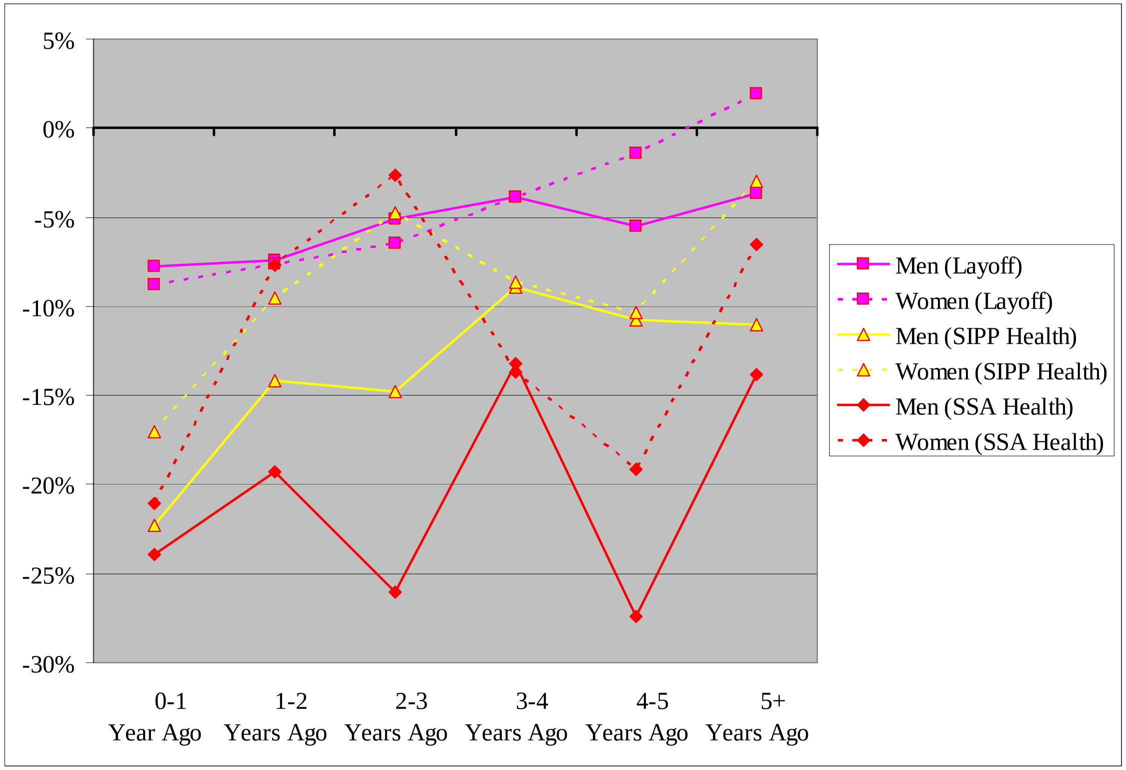

Figure 1.10: Percent Effect of Exogenous Layoff and Health Shocks on Hourly Wage Rate by Gender

job because of illness. The SSA measures of disability provide the least optimistic interpretation of recovery: men spend 9.3% fewer hours at work in the initial year back, which falls another 3% after four years. For women with these measures, 5% to 9% fewer hours are worked in the first two years after a health shock. Thereafter, women appear to have recovered and are even more present at work than the nondisplaced population, working 3% more hours after five years have passed according to SIPP survey measures.

Overall, reductions to hourly wage rates are the most substantial when a match was terminated because of reasons relating to ill health. Males are acutely burdened within their first year back, with wage rates that are 77.8% of their previous values in the SIPP-based model. Women experience a 17% decrease in their wages the year of the onset of a disabling condition, but this improves to a wage loss of 9.6% after an additional year while men experience earnings that are 85.8% of their predisplacement wage rate in the same period.

The restricted sample based upon the SIPP measures reflects a highly identical pattern for men, while the recovery for women in the first few years after the date of the event is greater, rising to 90.4% of the wage rate after one year. The measures from administrative benefits records demonstrate a more troubling period of recovery for both men and women. The impact on the hourly wage of men fluctuates, ranging from -13.2% of the predisplacement value the third year after the event to around -27% in the surrounding years. The rate for women also exhibits signs of a resurgence in the fourth year, where it remains 19.1% below what it would have otherwise been. Convincing evidence of the severity of the lasting effects of a health shock upon the hourly wage rates exists for both genders.

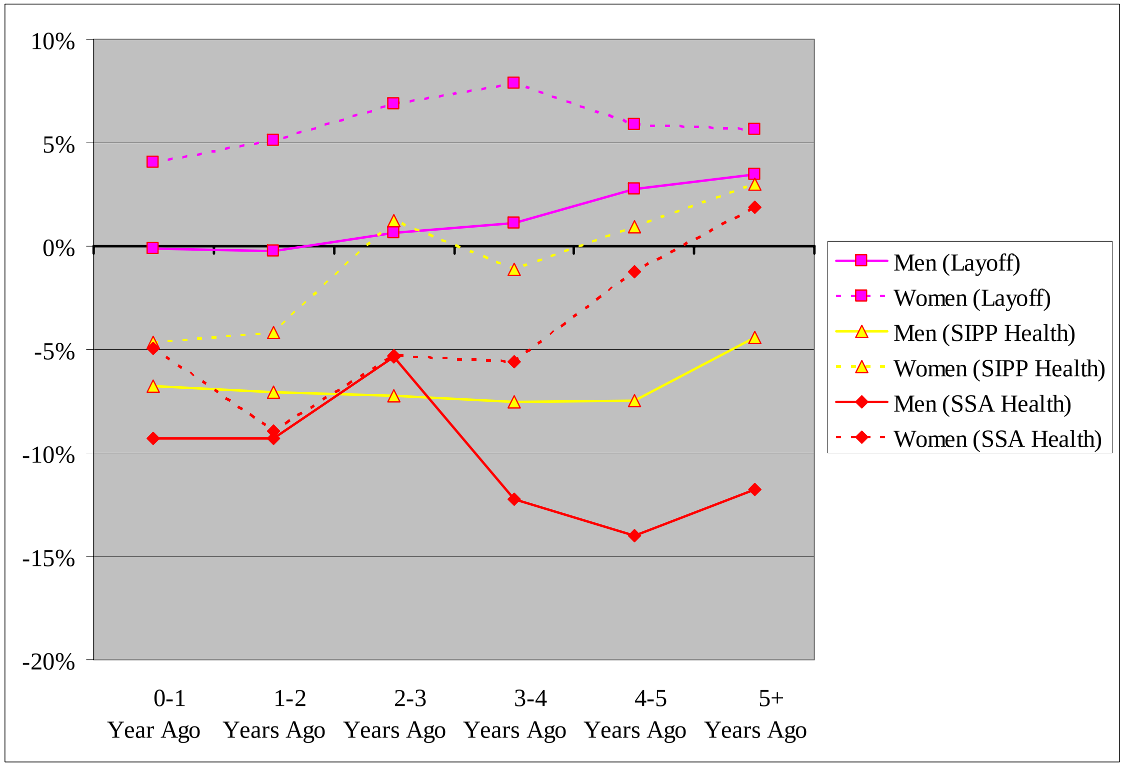

Figure 1.11: Percent Effect of Exogenous Layoff and Health Shocks on Weekly Hours by Gender

Race In the case of weekly hours of those who have suffered a layoff, Tables 1.18, 1.19, and 1.20 make it clear that a distinction between races exists, as nonwhites do not as significantly react to adjust their time spent at work. In the initial year back at work after a layoff, whites work 1.5% more hours each week than do the nondisplaced. Five years later, this percentage for whites has gradually risen to 4.6%. However, it is only in the third year that nonwhites have weekly hours that noticeably differ their pre-shock value. During that period, they spend 3.8% more time at work than do those with continuous employment.

A longer work week may be one way that whites who were laid off compensate for having accepted new positions at lower hourly wage rates. Whites, who consistently work more following a layoff, experience wage rate losses that are similar to nonwhites in the first four years after the event. They earn 91.6% of their predisplacement wage rates within the first year after a layoff. Nonwhites are affected only slightly less over same time period, having a wage rate that is 92.9%. During the four years subsequent to a forced exist of this type, nonwhites and whites consistently reduce the negative impacts from having been once laid off as their wage rates improve 1-3 percentage points each year. The determination of Ong (1991) that blacks, upon being rehired, have yearly earnings that are 96.9% those of whites who have found new jobs is not ruled out by these findings. This is because the cumulative impact on weekly wages for whites and nonwhites ranges from no noticeable difference in the year of the event to between 1.7% to 3.9% during the next two years.

For those with employer-employee separations induced by a disabling condition, nonwhites suffer more in terms of the level of exertion on the job within the first year back than do whites. Whites work 5.3% less and nonwhites work 9.1% fewer

Table 1.18: Joint Estimation of Wage and Hours by Race for the Restricted Sample (SIPP Health Measures)

	Restricted SIPP Health Measures			
	Hourly Wage		**Weekly Hours**	
	White	**Nonwhite**	**White**	**Nonwhite**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2214 ***	-0.1892 ***	-0.0548 ***	-0.0951 ***
	(0.0101)	(0.0327)	(0.0069)	(0.0229)
1-2 Years Ago	-0.1210 ***	-0.1471 ***	-0.0659 ***	-0.0071
	(0.0103)	(0.0286)	(0.0063)	(0.0181)
2-3 Years Ago	-0.1079 ***	-0.0703	-0.0373 ***	0.0112
	(0.0102)	(0.0441)	(0.0070)	(0.0258)
3-4 Years Ago	-0.0999 ***	-0.0884 *	-0.0428 ***	-0.0459
	(0.0119)	(0.0358)	(0.0069)	(0.0274)
4-5 Years Ago	-0.1318 ***	-0.0515	-0.0463 ***	0.0529
	(0.0146)	(0.0633)	(0.0100)	(0.0296)
5+ Years Ago	-0.0789 ***	-0.0076	-0.0237 *	0.0796 **
	(0.0168)	(0.0828)	(0.0113)	(0.0302)
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0879 ***	-0.0733 ***	0.0145 ***	-0.0035
	(0.0052)	(0.0135)	(0.0030)	(0.0160)
1-2 Years Ago	-0.0784 ***	-0.0811 ***	0.0142 ***	0.0176
	(0.0050)	(0.0137)	(0.0029)	(0.0162)
2-3 Years Ago	-0.0574 ***	-0.0667 ***	0.0293 ***	0.0076
	(0.0052)	(0.0138)	(0.0029)	(0.0155)
3-4 Years Ago	-0.0405 ***	-0.0387 *	0.0322 ***	0.0374 *
	(0.0055)	(0.0150)	(0.0029)	(0.0159)
4-5 Years Ago	-0.0301 ***	-0.0974 ***	0.0392 ***	0.0115
	(0.0061)	(0.0168)	(0.0032)	(0.0163)
5+ Years Ago	-0.0131 *	-0.0271	0.0451 ***	-0.0003
	(0.0063)	(0.0189)	(0.0033)	(0.0177)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3140		0.1755	
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3053		0.2025	
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4837			
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3507		0.4103	
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2611			
Number of Workers	28,164			
Number of Jobs	50,833			
ln-L	-131,055.23			

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.19: Joint Estimation of Wage and Hours by Race for the Restricted Sample (SSA Health Measures)

	Restricted SSA Health Measures			
	Hourly Wage		Weekly Hours	
	White	**Nonwhite**	**White**	**Nonwhite**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2346 ***	-0.2712 ***	-0.0635 ***	-0.1908 ***
	(0.0184)	(0.0795)	(0.0110)	(0.0406)
1-2 Years Ago	-0.1268 ***	-0.2193	-0.1118 ***	0.0295
	(0.0185)	(0.1150)	(0.0091)	(0.0312)
2-3 Years Ago	-0.1825 ***	-0.1663 *	-0.0583 **	-0.0165
	(0.0183)	(0.0841)	(0.0184)	(0.0409)
3-4 Years Ago	-0.1342 ***	-0.1487	-0.1049 ***	-0.0515
	(0.0218)	(0.1654)	(0.0185)	(0.1380)
4-5 Years Ago	-0.2641 ***	-0.0661	-0.1223 ***	0.2463
	(0.0293)	(0.2563)	(0.0249)	(0.1691)
5+ Years Ago	-0.1042 *	0.0527	-0.0902 ***	0.3183 **
	(0.0434)	(0.1610)	(0.0258)	(0.1188)
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0913 ***	-0.0735 ***	0.0141 ***	-0.0039
	(0.0052)	(0.0136)	(0.0030)	(0.0161)
1-2 Years Ago	-0.0814 ***	-0.0812 ***	0.0138 ***	0.0170
	(0.0050)	(0.0138)	(0.0029)	(0.0163)
2-3 Years Ago	-0.0601 ***	-0.0666 ***	0.0288 ***	0.0076
	(0.0052)	(0.0139)	(0.0029)	(0.0156)
3-4 Years Ago	-0.0430 ***	-0.0383 *	0.0318 ***	0.0365 *
	(0.0054)	(0.0151)	(0.0029)	(0.0161)
4-5 Years Ago	-0.0323 ***	-0.0968 ***	0.0388 ***	0.0108
	(0.0061)	(0.0169)	(0.0032)	(0.0164)
5+ Years Ago	-0.0150 *	-0.0265	0.0446 ***	-0.0011
	(0.0063)	(0.0190)	(0.0033)	(0.0178)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3139		0.1755	
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3076		0.2028	
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4863			
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3508		0.4102	
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2608			
Number of Workers	28,164			
Number of Jobs	50,833			
ln-L	-131,144.52			

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.20: Percent Effect of Exogenous Health and Layoff Shocks on Hourly Wage and Weekly Hours by Race- Significant Values Only

	Restricted SIPP Health Measures			
	Hourly Wage		**Weekly Hours**	
	White	**Nonwhite**	**White**	**Nonwhite**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.1986	-0.1724	-0.0533	-0.0907
1-2 Years Ago	-0.1140	-0.1368	-0.0638	-
2-3 Years Ago	-0.1023	-	-0.0366	-
3-4 Years Ago	-0.0951	-0.0846	-0.0419	-
4-5 Years Ago	-0.1235	-	-0.0452	-
5+ Years Ago	-0.0759	-	-0.0234	0.0829
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0841	-0.0707	0.0146	-
1-2 Years Ago	-0.0754	-0.0779	0.0143	-
2-3 Years Ago	-0.0558	-0.0645	0.0297	-
3-4 Years Ago	-0.0397	-0.0380	0.0327	0.0381
4-5 Years Ago	-0.0297	-0.0928	0.0400	-
5+ Years Ago	-0.0130	-	0.0461	-

	Restricted SSA Health Measures			
	Hourly Wage		**Weekly Hours**	
	White	**Nonwhite**	**White**	**Nonwhite**
Own Exogenous Health Shock:				
0-1 Year Ago	-0.2091	-0.2375	-0.0615	-0.1737
1-2 Years Ago	-0.1191	-	-0.1058	-
2-3 Years Ago	-0.1668	-0.1532	-0.0566	-
3-4 Years Ago	-0.1256	-	-0.0996	-
4-5 Years Ago	-0.2321	-	-0.1151	-
5+ Years Ago	-0.0990	-	-0.0863	0.3748
Own Exogenous Layoff Shock:				
0-1 Year Ago	-0.0873	-0.0709	0.0142	-
1-2 Years Ago	-0.0782	-0.0780	0.0139	-
2-3 Years Ago	-0.0583	-0.0644	0.0292	-
3-4 Years Ago	-0.0421	-0.0376	0.0323	0.0372
4-5 Years Ago	-0.0318	-0.0923	0.0396	-
5+ Years Ago	-0.0149	-	0.0456	-

Note: The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: e^{δ}-1.

hours when using measures of health shocks derived from the demographic survey data. When administrative measures are used in their place, these percentages drop further to -6.2% and -17.4% for whites and nonwhites. The amount of time spent at a job varies with the number of years since the dislocation. Nonwhites are able to begin to work additional hours five years or more since the event, improving their hours by 8.2% when using SIPP health measures and a surprising 37.5% above the number of hours for a worker without a health exit when SSA measures are utilized. Whites exhibit recovery their weekly hours at work over the years, but these are not as impressive as the improvements of nonwhites.

Reductions to hourly wage rates are substantial when a match was terminated because of reasons relating to ill health. Whites are more acutely burdened than nonwhites within their first year back except in the sample using administrative measures of disability. Wages are found to be 80.1% of their previous values for whites when referencing the restricted SIPP shock indicators. By comparison, nonwhite wages are around 82.8% of what they would otherwise have been. Using measures of disability from the Social Security Administration, wage rates are 79.1% and 76.3% for whites and nonwhites within one year of the onset of a disabling condition.

Both races begin to exhibit improvements to their wage rates after the first year since poor health caused a forced exit. The lingering effects of a displacing health condition upon the hourly wage rate of whites is apparent in Table 1.20, as five years after the event earnings are around 92.4% in the subset based on demographic indicators of health limitations and 90.1% for this sample based upon the administrative evidence of poor health. The lasting impacts for nonwhites is not significant five years or more after the shock.

This analysis of racial differences in reactions to displacement illustrate key disparities in the weekly hours of those with past layoffs. Results also indicate that while whites and nonwhites fare comparably within the year of the job separation, thereafter nonwhites appear to recoup losses at a slower rate. A decomposition in the racial gap in the post-displacement outcomes following Fairlie and Kletzer (1998) would be beneficial in further parsing the reasons behind these dissimilarities.

1.5.2 Spousal Job Displacements

Only workers who were married for the duration of the panel and whose spouses were also participants in the Survey of Income and Program Participation are included in the proportional hazard and joint estimation of the wage rate and weekly hours.[31] Each model is examined using this full sample of paired couples and a restricted sample. This examination focuses on the lingering impacts of exogenous separations of the spouse rather than of the worker herself, and as such the limited sample becomes one defined by the eligibility of the spouse to apply for disability insurance benefits. This makes it possible to interpret results for spouses who might not ordinarily have been in the labor force.

I begin by reviewing summary statistics for the married workers.[32] Table 1.21

[31] Additional exclusions include household workers, armed forces personnel, unemployed military personnel, those with job spans lasting less than one day, those with allocated responses, those younger than 21 or older than 60, those with spouses who are younger than 21 or older than 60, those with weekly hours less than or equal to zero or a real hourly wage of less than \$0.10, and those who are not original sample members.

[32] The restricted sample is limited to those individuals with spouses who have a Social Security Number associated with their SIPP internal identification number. Only those workers with spouses who are additionally eligible to apply for SSDI benefits in the given month are included in this sample.

reveals that the unrestricted sample is composed of 7,671 individuals covering 12,398 jobs; the restricted spouse sample has 6,294 individuals with 10,089 jobs. The full sample is 50.1% male, but restricting based on spousal eligibility for SSDI increases the number of women in the sample to 53.3%. Married workers are more educated than the overall population in Table 1.1, and those with spouses who are highly attached to the work force on average have spent more time in school. Job characteristics do not differ greatly, with the mean hourly wage $0.24 less in the restricted spouse sample.

The timing of the exogenous shocks are presented in Table 1.22, by sample, type of event, and affected spouse.[33] More husbands have wives who have applied for SSDI benefits within the past two years, but women have nearly twice as many partners with administrative records of ailments that date from more than two years ago. Survey measures of impairments across genders are fairly similar, while layoffs appear to impact men more frequently.

Tables 1.23 and 1.24 are of the Pearson correlation coefficients for the survey and administrative health shock indicators of wives and husbands of the employed. Coefficients range between 0.32 and 0.45 along the diagonal for men with displaced wives and between 0.38 and 0.44 for women with spouses who have exited. The correlations in Table 1.24 are greater than those presented in Table 1.5 for the restricted sample of all workers, and indicate the higher reliability of the survey

[33]Excluded are household workers, armed forces personnel, unemployed military personnel, those with job spans lasting less than one day, those with allocated responses, those younger than 21 or older than 60, those with weekly hours equal to zero or hourly wages in constant 2003 dollars of less than $0.10, and those who are not original sample members. In the unrestricted sample, 85,483 male worker observations and 80,455 female worker observations exist for all individuals over all time periods; in the restricted spouse sample, 66,016 male and 71,184 female worker observations exist.

Table 1.21: Married Individual's Worker and Job Summary Statistics

	Unrestricted Sample			Restricted Spouse Sample		
	Obs	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Worker Characteristics:						
White	7,671	0.8913	20.8497	6,294	0.8985	20.1797
Hispanic	7,671	0.0925	19.4093	6,294	0.0860	18.7367
Male	7,671	0.5055	33.4927	6,294	0.4674	33.3469
Education:						
Years	7,671	13.4829	192.3507	6,294	13.5026	186.6202
High School	7,671	0.3280	31.4508	6,294	0.3356	31.5609
Some College	7,671	0.2618	29.4510	6,294	0.2682	29.6083
College Degree	7,671	0.1464	23.6787	6,294	0.1481	23.7410
Graduate Schooling	7,671	0.1457	23.6367	6,294	0.1398	23.1798
Time-Varying Worker Characteristics:						
Number of Children	165,938	1.4681	82.5183	137,200	1.4121	79.9332
Health Insurance Under Another's Plan	165,938	0.2832	30.6364	137,200	0.3042	31.2212
Job Characteristics:						
Number of Jobs	12,398	1.7882	72.6145	10,089	1.7657	70.5753
Union Member	12,398	0.1562	24.0152	10,089	0.1481	23.4621
Job Type:						
Private, Not-for-Profit, Tax Exempt, or Charitable	12,398	0.0565	15.2765	10,089	0.0592	15.5866
Government	12,398	0.1394	22.9088	10,089	0.1338	22.4886
Industry:						
Agriculture and Forestry/Fisheries	12,398	0.0195	9.1553	10,089	0.0174	8.6334
Mining	12,398	0.0042	4.2719	10,089	0.0040	4.1918
Construction	12,398	0.0782	17.7612	10,089	0.0699	16.8376
Manufacturing	12,398	0.1479	23.4865	10,089	0.1479	23.4447
Trans., Comm., and Public Utilities	12,398	0.0563	15.2520	10,089	0.0521	14.6836
Wholesale Trade	12,398	0.0429	13.3988	10,089	0.0428	13.3625
Retail Trade	12,398	0.1753	25.1515	10,089	0.1821	25.4924
FIRE	12,398	0.0605	15.7653	10,089	0.0606	15.7610
Business and Repair Services	12,398	0.3756	32.0346	10,089	0.3834	32.1139
Public Administration	12,398	0.0374	12.5457	10,089	0.0374	12.5252
Time-Varying Job Characteristics:						
Hourly Wage ($2003)	165,938	16.29	1,511.25	137,200	16.05	1,570.01
Weekly Hours	165,938	38.7895	835.5496	137,200	38.4684	837.3836
Months of Experience	165,938	204.6486	6,861.2500	137,200	203.0417	6,828.9200

Table 1.22: Summary of the Timing of Exogenous Shocks of Worker and Spouse

	Unrestricted Married Sample		**Restricted Spouse Sample**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
SIPP Layoff Shock:				
Of Wife				
0-1 Year Ago	0.0637	16.7934	0.0636	16.7340
1-2 Years Ago	0.0243	10.5859	0.0258	10.8659
2+ Years Ago	0.0706	17.6193	0.0757	18.1401
Of Husband				
0-1 Year Ago	0.0948	19.6793	0.0962	19.8135
1-2 Years Ago	0.0357	12.4636	0.0374	12.7556
2+ Years Ago	0.1128	21.2494	0.1137	21.3318
SIPP Health Shock:				
Of Wife				
0-1 Year Ago	0.0357	12.7610	0.0302	11.7338
1-2 Years Ago	0.0088	6.4069	0.0084	6.2555
2+ Years Ago	0.0207	9.7856	0.0200	9.5897
Of Husband				
0-1 Year Ago	0.0286	11.1903	0.0306	11.5745
1-2 Years Ago	0.0067	5.4713	0.0068	5.5108
2+ Years Ago	0.0203	9.4835	0.0201	9.4395
SSA Health Shock:				
Of Wife				
0-1 Year Ago	-	-	0.0114	7.2731
1-2 Years Ago	-	-	0.0026	3.4920
2+ Years Ago	-	-	0.0026	3.4823
Of Husband				
0-1 Year Ago	-	-	0.0098	6.6350
1-2 Years Ago	-	-	0.0014	2.5559
2+ Years Ago	-	-	0.0052	4.8105

Table 1.23: Pearson Correlation Coefficients for SIPP-based Health Shocks of Spouses of Married Male Workers

	SIPP Health Shock of Wife		
SSA Health Shock of Wife	**0-1 Year Ago**	**1-2 Years Ago**	**2+ Years Ago**
0-1 Year Ago	**0.4483**	0.1119	0.0766
	<.0001	<.0001	<.0001
1-2 Years Ago	0.0743	**0.3687**	0.0763
	<.0001	<.0001	<.0001
2+ Years Ago	0.0244	0.0249	**0.3150**
	<.0001	<.0001	<.0001

Note: Correlation coefficients are presented along with the p-values under the hypothesis that ρ=0. The restricted sample of 66,016 observations is used.

Table 1.24: Pearson Correlation Coefficients for SSA-based Health Shocks of Spouses of Married Female Workers

	SIPP Health Shock of Husband		
SSA Health Shock of Husband	**0-1 Year Ago**	**1-2 Years Ago**	**2+ Years Ago**
0-1 Year Ago	**0.4324**	0.0209	0.0223
	<.0001	<.0001	<.0001
1-2 Years Ago	0.0037	**0.3772**	-0.0054
	0.3271	<.0001	0.1463
2+ Years Ago	-0.0066	-0.0059	**0.4417**
	0.0770	0.1138	<.0001

Note: Correlation coefficients are presented along with the p-values under the hypothesis that ρ=0. The restricted sample of 71,184 observations is used.

measures.

Proportional Hazard

Hazard ratios of the effect of spousal shocks on the job spell duration of married workers are presented in Table 1.25.[34] These ratios represent the probability of a married worker whose spouse experienced an exogenous health or layoff shock 0-1 years ago, 1-2 years ago, and 2 or more years ago leaving a job relative to this probability for an otherwise identical married worker with a spouse who has

[34] Hazard ratios are the exponentiation of the coefficients from the hazard model.

never experienced a shock. Employees with spouses without such events in their work history comprise the baseline for this comparison. A hazard ratio greater than one means that the event has a positive influence on the hazard of a job spell concluding, whereas a ratio less than one means that the event has a negative effect on the termination of the job.

Married male workers do not appear to be greatly affected by the layoffs of their wives, while women with husbands who have suffered from a layoff only experience a 13% decrease in the hazard of their job ending two years after the event. Disabling health shocks, however, have more interesting repercussions, as is apparent in Figures 1.12 and 1.13. Women with husbands who experience disabling health shocks have a 40.7% increase in the hazard of their current job ending when referencing the results from the unrestricted sample. Two or more years after the date of a husband's job exit induced by ill health, the hazard of the wife's job ending is 76% that of the baseline worker's hazard, which is a 24% reduction in the hazard. These findings do not greatly differ for the restricted sample with SIPP health measures. However, the restricted subset that utilizes SSA-based measures demonstrates a 46.5% increase in the hazard of a job ending within the first year of a husband's health shock. This is consistent with a withdrawal from the labor force. Coile (2004) discovered that women decrease their labor supply subsequent to the unexpected and severe onset of a crippling ailment of their husbands, which supports this conclusion.

The unrestricted sample shows that married men with wives who experienced an unexpected disabling condition in the previous year have job hazards that are 47.8% more than those of the baseline married employee. The restricted spouse sample that utilizes the SIPP measures of health indicates that this hazard is 32.1%

Table 1.25: Hazard Ratios of the Effect of Spousal Shocks on the Job Spell Duration of Married Workers

	Unrestricted Married Sample	**Restricted Spouse Sample**	
	SIPP Health Measures	**SIPP Health Measures**	**SSA Health Measures**
Exogenous Health Shock of Wife:			
0-1 Year Ago	1.4779 ***	1.3206 ***	1.1061
	(0.0741)	(0.1075)	(0.2724)
1-2 Years Ago	1.3395 *	1.6472 ***	1.7876
	(0.1505)	(0.1592)	(0.3762)
2+ Years Ago	0.9989	0.9892	1.2082
	(0.1108)	(0.1365)	(0.2761)
Exogenous Layoff Shock of Wife:			
0-1 Year Ago	1.1893 ***	1.1282	1.1093
	(0.0668)	(0.0755)	(0.0771)
1-2 Years Ago	1.0457	1.0466	1.0579
	(0.1038)	(0.1145)	(0.1135)
2+ Years Ago	0.9635	0.9099	0.9090
	(0.0667)	(0.0739)	(0.0741)
Exogenous Health Shock of Husband:			
0-1 Year Ago	1.4068 ***	1.3989 ***	1.4651 **
	(0.0958)	(0.0997)	(0.1548)
1-2 Years Ago	1.0935	1.1307	1.0381
	(0.1964)	(0.2112)	(0.4129)
2+ Years Ago	0.7603 **	0.6958 **	0.6067
	(0.1282)	(0.1481)	(0.3186)
Exogenous Layoff Shock of Husband:			
0-1 Year Ago	1.0475	1.0170	1.0211
	(0.0595)	(0.0651)	(0.0650)
1-2 Years Ago	1.0862	1.0279	1.0441
	(0.0826)	(0.0904)	(0.0910)
2+ Years Ago	0.8689 **	0.8587 **	0.8689 **
	(0.0578)	(0.0615)	(0.0616)
Stdev. Person Effects: σ_ν	0.3169	0.2623	0.2635
Number of Individuals	7,671	6,294	6,294
Number of Spells	12,398	10,089	10,089
ln-L	-51,332.33	-41,705.75	-41,716.31

Note: Hazard ratios are the exponentiation of the coefficients from the hazard model.

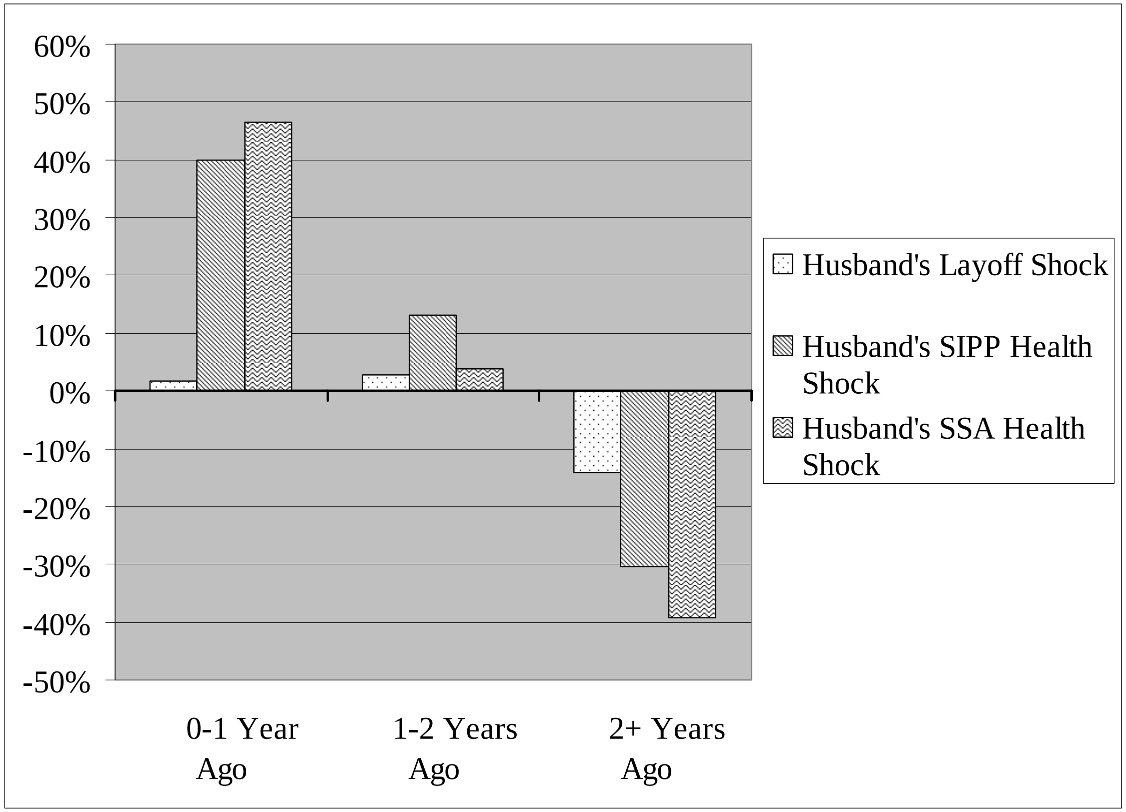

Figure 1.12: Percent Effect of Husband's Shock on Wife's Hazard of Job Ending

Figure 1.13: Percent Effect of Wife's Shock on Husband's Hazard of Job Ending

above that of the baseline worker, which doubles in the next year. It is apparent that spouses who are married to individuals who experience a health exit are also transitioning out of their jobs. This may be to unemployment so that they can assist in nursing duties, or they may be accepting more flexible positions. After two years or more have passed since either type of displacing event, wives are more attached to their jobs. Men in the restricted sample appear to be unaffected by the layoffs of their wives according to this duration analysis. However, they are more inclined to part with their employers in each of the first two years following an exogenous health shock to their wives.

This confirms the results of Charles (1999) that husbands are less likely to be employed when their spouses are disabled. He explains that women are more inclined to work for pay in an identical situation. Because Charles' estimations do not attempt to parse the adjustment effects of illness, his claims support the conclusions I have made regarding the behaviors of wives two years or more after their husbands' health-related job separations. The observed reductions in the hazard after a few years since either the onset of the work limiting condition or the layoff of the husband also suggest that health insurance provided by the female's employer has by this time become particularly valuable. This is consistent with Blau (1998), who found that the poor health of an unemployed husband of a working wife reduces her exit rate by 16% compared to wives of unemployed men who are in good health. Families with a male member who has been forced out of the work force may be shifting coverage to the female partner in the couple after two years.

Joint Model

The joint model of hourly wages and weekly hours of married individuals contributes to knowledge of how a couple is affected as a unit by dislocations. The ideas presented by the estimation of the proportional hazard model in Table 1.25 regarding spell durations of employer-employee matches relate to the concepts revealed by the estimation of this model outlined in Table 1.29, which summarizes Tables 1.26-1.28.

Men and women with spouses who have become unemployed because of a layoff behave quite differently from each other, as is apparent from Figures 1.14-1.17. The hours of working husbands are not significantly altered by firm-side exits of their wives at any time during the ensuing years while women work more. Working husbands of laid off wives have wages that are 4.8% above the rates of employees without displaced partners in the second year after separation in the restricted sample, whereas wives in this subset have rates that are diminished by 2.3%.

The reductions in the hourly wage rates of the spouse of a disabled individual in Tables 1.33 and 1.34 (summarizing Tables 1.30-1.32) appear to be related to either job changes or to temporary new positions[35] as observed in Table 1.25. For husbands whose wives experienced an episode of ill health within the previous year, wages are around 92% of their value and hours are reduced by 5.9% when utilizing SIPP measures in the restricted sample. Health status derived from ben-

[35]A job transition may occur after the spouse realizes that she needs to adapt her work schedule to accomodate the needs of her ailing partner. For a person who was not previously in the work force, the onset of her spouse's disabling condition may cause her to seek out new employment for a brief duration to temper the short-run impact of her mate's sudden loss of income until he recovers and is able to return to work. Either scenario can be used to explain the results from the hazard model.

Table 1.26: Joint Estimation of Wage and Hours with Heterogeneity in the Unrestricted Sample of Married Workers- Spousal Shocks

	SIPP Health Measures	
	Hourly Wage	**Weekly Hours**
Exogenous Health Shock of Wife:		
0-1 Year Ago	-0.0847 ***	-0.0523 ***
	(0.0177)	(0.0095)
1-2 Years Ago	-0.0418 **	-0.0342 ***
	(0.0160)	(0.0093)
2+ Years Ago	-0.0338	-0.0117
	(0.0181)	(0.0106)
Exogenous Layoff Shock of Wife:		
0-1 Year Ago	-0.0278 *	0.0139
	(0.0130)	(0.0127)
1-2 Years Ago	0.0222	-0.0070
	(0.0114)	(0.0117)
2+ Years Ago	0.0388 ***	-0.0018
	(0.0110)	(0.0115)
Exogenous Health Shock of Husband:		
0-1 Year Ago	-0.0591 **	-0.0285 ***
	(0.0183)	(0.0073)
1-2 Years Ago	-0.0263	-0.0743 ***
	(0.0159)	(0.0040)
2+ Years Ago	-0.0247	-0.0731 ***
	(0.0196)	(0.0061)
Exogenous Layoff Shock of Husband:		
0-1 Year Ago	-0.0346 ***	0.0064
	(0.0090)	(0.0046)
1-2 Years Ago	-0.0254 **	0.0202 ***
	(0.0089)	(0.0043)
2+ Years Ago	0.0074	0.0458 ***
	(0.0088)	(0.0042)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3160	0.1765
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3319	0.2454
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.5103	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3550	0.3954
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2321	
Number of Workers	7,671	
Number of Jobs	12,398	
ln-L	-49,793.82	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.27: Joint Estimation of Wage and Hours with Heterogeneity in the Restricted Sample of Married Workers- Spousal Shocks (SIPP Health Measures)

	SIPP Health Measures	
	Hourly Wage	**Weekly Hours**
Exogenous Health Shock of Wife:		
0-1 Year Ago	-0.0873 ***	-0.0608 ***
	(0.0226)	(0.0129)
1-2 Years Ago	-0.0477 *	-0.0499 ***
	(0.0237)	(0.0111)
2+ Years Ago	-0.0411	-0.0032
	(0.0244)	(0.0151)
Exogenous Layoff Shock of Wife:		
0-1 Year Ago	0.0039	0.0237
	(0.0162)	(0.0154)
1-2 Years Ago	0.0468 **	-0.0022
	(0.0143)	(0.0143)
2+ Years Ago	0.0552 ***	0.0018
	(0.0136)	(0.0142)
Exogenous Health Shock of Husband:		
0-1 Year Ago	-0.0492 *	-0.0254 **
	(0.0193)	(0.0085)
1-2 Years Ago	-0.0163	-0.0812 ***
	(0.0165)	(0.0041)
2+ Years Ago	-0.0111	-0.0977 ***
	(0.0206)	(0.0064)
Exogenous Layoff Shock of Husband:		
0-1 Year Ago	-0.0227 *	0.0100 *
	(0.0095)	(0.0050)
1-2 Years Ago	-0.0231 *	0.0244 ***
	(0.0094)	(0.0047)
2+ Years Ago	0.0090	0.0548 ***
	(0.0092)	(0.0047)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3158	0.1783
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3306	0.2450
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.5310	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3525	0.4002
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2363	
Number of Workers	6,294	
Number of Jobs	10,089	
ln-L	-42,475.01	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.28: Joint Estimation of Wage and Hours with Heterogeneity in the Restricted Sample of Married Workers- Spousal Shocks (SSA Health Measures)

	SSA Health Measures	
	Hourly Wage	**Weekly Hours**
Exogenous Health Shock of Wife:		
0-1 Year Ago	-0.1282 *	-0.1026 *
	(0.0509)	(0.0430)
1-2 Years Ago	-0.0816	-0.0415
	(0.0496)	(0.0319)
2+ Years Ago	-0.0172	0.0410
	(0.0584)	(0.0518)
Exogenous Layoff Shock of Wife:		
0-1 Year Ago	0.0046	0.0247
	(0.0163)	(0.0154)
1-2 Years Ago	0.0471 **	-0.0015
	(0.0143)	(0.0142)
2+ Years Ago	0.0556 ***	0.0024
	(0.0137)	(0.0142)
Exogenous Health Shock of Husband:		
0-1 Year Ago	-0.1990 ***	-0.1521 ***
	(0.0594)	(0.0266)
1-2 Years Ago	-0.2231 ***	-0.1804 ***
	(0.0594)	(0.0255)
2+ Years Ago	-0.0511	-0.4036 ***
	(0.1122)	(0.0264)
Exogenous Layoff Shock of Husband:		
0-1 Year Ago	-0.0231 *	0.0104 *
	(0.0095)	(0.0050)
1-2 Years Ago	-0.0233 *	0.0244 ***
	(0.0094)	(0.0047)
2+ Years Ago	0.0087	0.0540 ***
	(0.0092)	(0.0047)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3158	0.1783
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3304	0.2450
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.5310	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3526	0.4003
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2363	
Number of Workers	6,294	
Number of Jobs	10,089	
ln-L	-42,451.65	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.29: Percent Effect of Exogenous Health and Layoff Shocks of Spouse on the Hourly Wage and Weekly Hours of Married Workers- Significant Values Only

	Unrestricted Married Sample		**Restricted Spouse Sample**			
	SIPP Health Measures		**SIPP Health Measures**		**SSA Health Measures**	
	Hourly Wage	**Weekly Hours**	**Hourly Wage**	**Weekly Hours**	**Hourly Wage**	**Weekly Hours**
Exogenous Health Shock of Wife:						
0-1 Year Ago	-0.0812	-0.0510	-0.0836	-0.0590	-0.1203	-0.0975
1-2 Years Ago	-0.0409	-0.0336	-0.0466	-0.0487	-	-
2+ Years Ago	-	-	-	-	-	-
Exogenous Layoff Shock of Wife:						
0-1 Year Ago	-0.0274	-	-	-	-	-
1-2 Years Ago	-	-	0.0479	-	0.0482	-
2+ Years Ago	0.0396	-	0.0568	-	0.0572	-
Exogenous Health Shock of Husband:						
0-1 Year Ago	-0.0574	-0.0281	-0.0480	-0.0251	-0.1805	-0.1411
1-2 Years Ago	-	-0.0716	-	-0.0780	-0.2000	-0.1651
2+ Years Ago	-	-0.0705	-	-0.0931	-	-0.3321
Exogenous Layoff Shock of Husband:						
0-1 Year Ago	-0.0340	-	-0.0224	0.0101	-0.0228	0.0105
1-2 Years Ago	-0.0251	0.0204	-0.0228	0.0247	-0.0230	0.0247
2+ Years Ago	-	0.0469	-	0.0563	-	0.0555

Note: The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: e^{δ}-1.

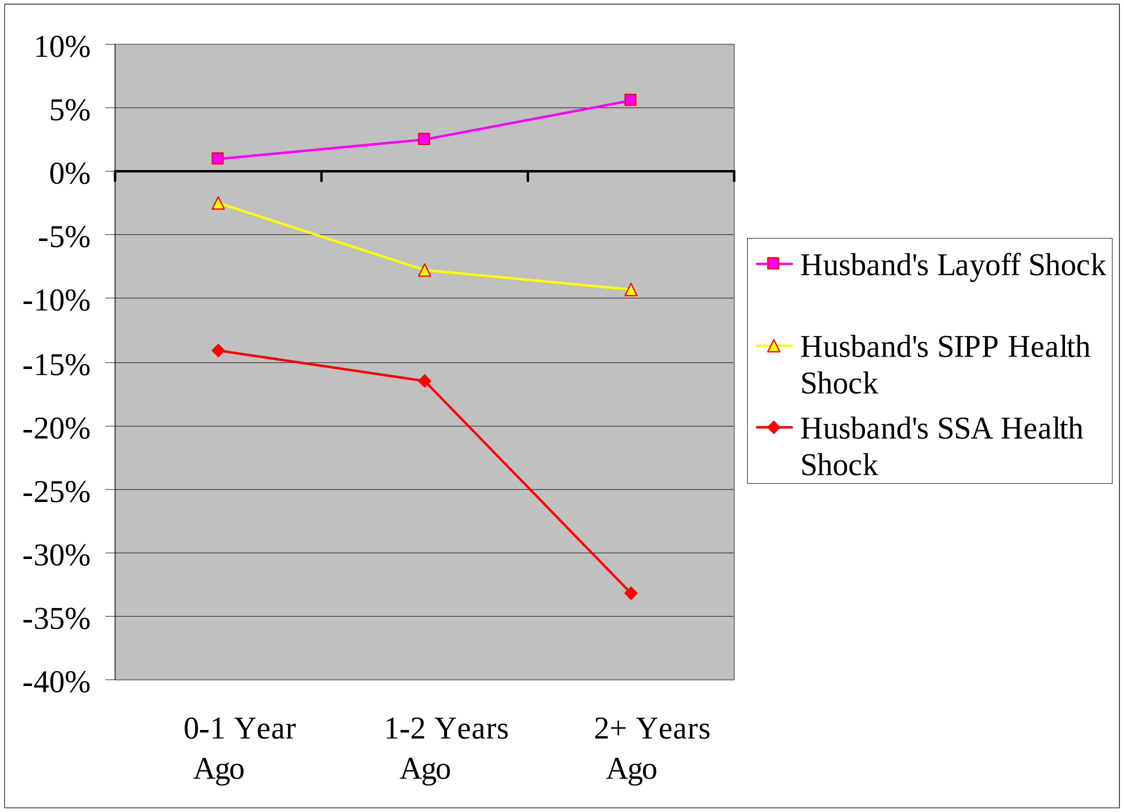

Figure 1.14: Percent Effect of Husband's Shock on Wife's Hourly Wage Rate

Figure 1.15: Percent Effect of Husband's Shock on Wife's Weekly Hours

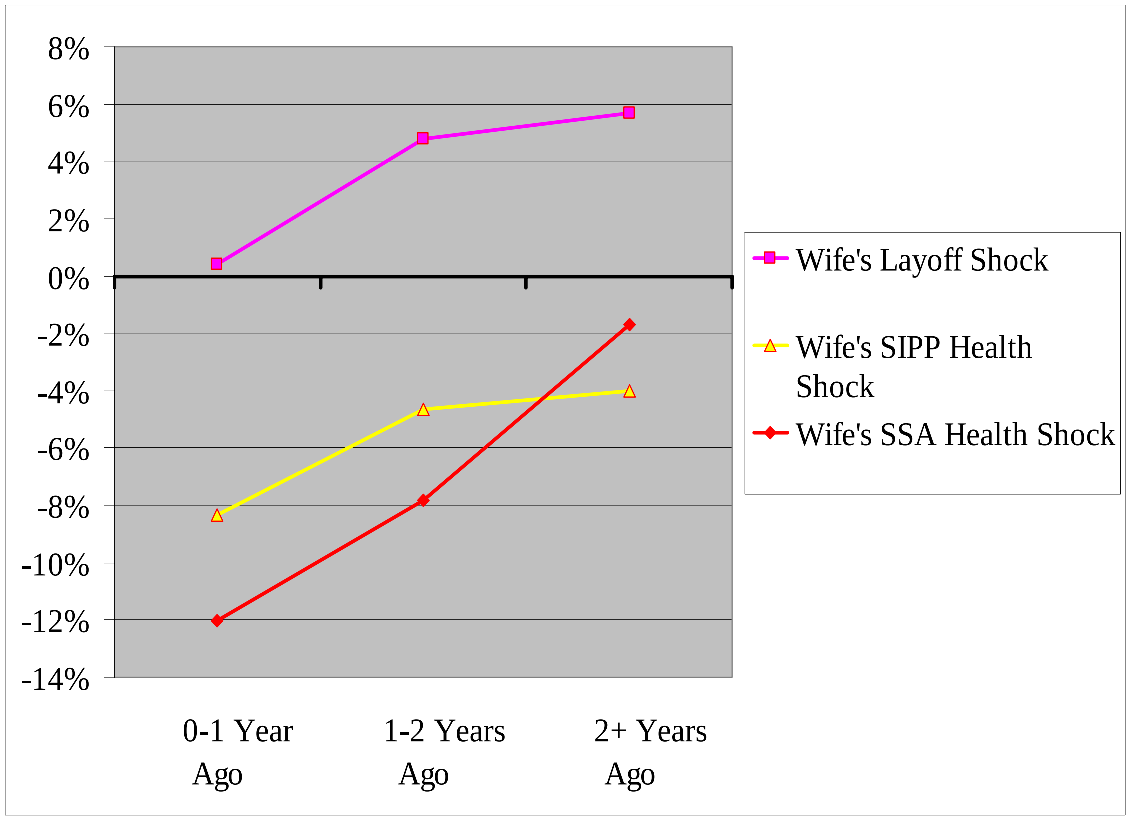

Figure 1.16: Percent Effect of Wife's Shock on Husband's Hourly Wage Rate

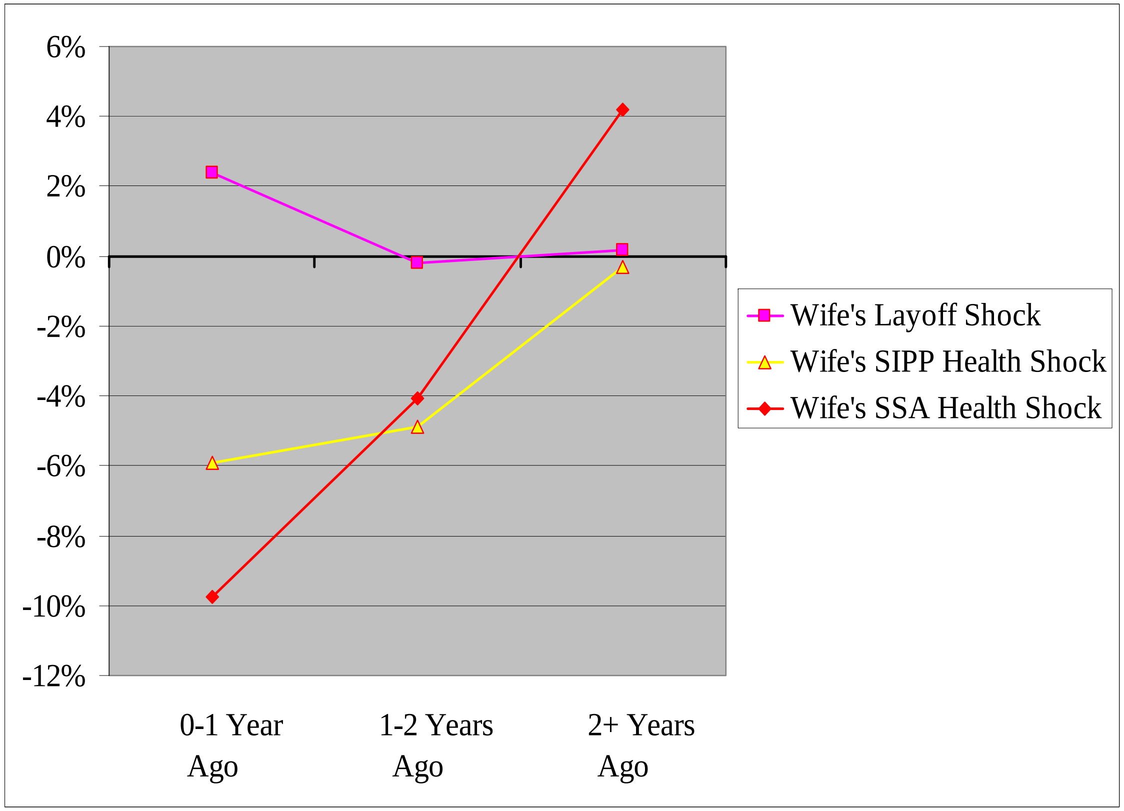

Figure 1.17: Percent Effect of Wife's Shock on Husband's Weekly Hours

efits records suggest that such men work 90.2% of their weekly hours prior to their wives' displacements. Restricted SIPP measures show that after the initial year, wives' hours at work move in the opposite direction of men with spouses in a symmetric situation: instead of improving, their weekly hours have fallen by another 5 percentage points. Captured within these actions is the apparent rationing of the productive hours of wives so that a portion of their time can be spent assisting in the nursing care of their ill spouses.

Administrative measures present evidence of the strength of spousal reactions to displacing health shocks: wages of women fall to 82% of the rates of workers without partners dislocated due to disability and worsen within a year. The reactions of the wives in a couple plagued by ill health are more exaggerated than those of their disabled partners, as seen by comparing Tables 1.27 and 1.28 with Tables 1.31 and 1.32. The wives have weekly hours that drop to 33.2% below the hours of workers of spouses who have consistently been well after two years. These are the most dramatic impacts seen and are indicative of the deteriorating health and advanced medical complications of the spouses of these employed workers.

The SIPP-based estimations have men reacting more strongly initially to their wives' health exits, as evidenced by the more dramatic decline of their wage rates and weekly hours within the first year of the episode. However, as time passes, these male workers begin to return to their previous levels of exertion and earnings, whereas wives with husbands who have experienced disabling shocks begin to take more time away from their jobs to presumably care for their ailing spouses. The model that relies upon administrative measures of well-being portrays a different story, as women are seen to be more reactive to the conditions that displaced their husbands even in the initial year.

Table 1.30: Joint Estimation of Wage and Hours with Heterogeneity in the Unrestricted Sample of Married Workers- The Effect of Own Shocks on Married Workers

	SIPP Health Measures	
	Hourly Wage	**Weekly Hours**
Own Exogenous Health Shock of Male Worker:		
0-1 Year Ago	-0.2687 ***	-0.0797 ***
	(0.0259)	(0.0196)
1-2 Years Ago	-0.1640 ***	-0.0517 **
	(0.0308)	(0.0166)
2+ Years Ago	-0.1656 ***	-0.0764 ***
	(0.0276)	(0.0180)
Own Exogenous Layoff Shock of Male Worker:		
0-1 Year Ago	-0.0609 ***	-0.0045
	(0.0099)	(0.0060)
1-2 Years Ago	-0.1025 ***	-0.0060
	(0.0097)	(0.0052)
2+ Years Ago	-0.0431 ***	0.0187 ***
	(0.0099)	(0.0050)
Own Exogenous Health Shock of Female Worker:		
0-1 Year Ago	-0.2031 ***	-0.0970 ***
	(0.0311)	(0.0146)
1-2 Years Ago	-0.1177 ***	-0.0342 **
	(0.0269)	(0.0133)
2+ Years Ago	-0.1119 ***	0.0695 ***
	(0.0275)	(0.0136)
Own Exogenous Layoff Shock of Female Worker:		
0-1 Year Ago	-0.0881 ***	0.0367 **
	(0.0152)	(0.0126)
1-2 Years Ago	-0.0492 **	0.0211
	(0.0154)	(0.0120)
2+ Years Ago	-0.0294	0.0581 ***
	(0.0156)	(0.0124)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3159	0.1764
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3272	0.2449
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.5131	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3551	0.3955
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2301	
Number of Workers	7,671	
Number of Jobs	12,398	
ln-L	-49,680.78	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.31: Joint Estimation of Wage and Hours with Heterogeneity in the Restricted Sample of Married Workers- The Effect of Own Shocks on Married Workers (SIPP Health Measures)

	SIPP Health Measures	
	Hourly Wage	**Weekly Hours**
Own Exogenous Health Shock of Male Worker:		
0-1 Year Ago	-0.2488 ***	-0.0962 ***
	(0.0270)	(0.0188)
1-2 Years Ago	-0.1792 ***	-0.0399 **
	(0.0316)	(0.0155)
2+ Years Ago	-0.1732 ***	-0.0670 ***
	(0.0282)	(0.0170)
Own Exogenous Layoff Shock of Male Worker:		
0-1 Year Ago	-0.0664 ***	-0.0055
	(0.0102)	(0.0057)
1-2 Years Ago	-0.1067 ***	-0.0069
	(0.0099)	(0.0049)
2+ Years Ago	-0.0591 ***	0.0163 ***
	(0.0102)	(0.0048)
Own Exogenous Health Shock of Female Worker:		
0-1 Year Ago	-0.2053 ***	-0.0466
	(0.0429)	(0.0286)
1-2 Years Ago	-0.0857 *	-0.0402
	(0.0359)	(0.0250)
2+ Years Ago	-0.0940 *	0.0559 *
	(0.0376)	(0.0250)
Own Exogenous Layoff Shock of Female Worker:		
0-1 Year Ago	-0.0969 ***	0.0383 **
	(0.0167)	(0.0135)
1-2 Years Ago	-0.0606 ***	0.0162
	(0.0170)	(0.0129)
2+ Years Ago	-0.0450 **	0.0529 ***
	(0.0171)	(0.0133)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3105	0.1694
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3189	0.2150
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.4982	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3487	0.3888
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2334	
Number of Workers	6,225	
Number of Jobs	10,120	
ln-L	-27,631.45	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.32: Joint Estimation of Wage and Hours with Heterogeneity in the Restricted Sample of Married Workers- The Effect of Own Shocks on Married Workers (SSA Health Measures)

	SSA Health Measures	
	Hourly Wage	**Weekly Hours**
Own Exogenous Health Shock of Male Worker:		
0-1 Year Ago	-0.2030 ***	-0.0859
	(0.0463)	(0.0588)
1-2 Years Ago	-0.1265 *	0.0665
	(0.0526)	(0.0467)
2+ Years Ago	-0.3399 ***	-0.0034
	(0.0627)	(0.1044)
Own Exogenous Layoff Shock of Male Worker:		
0-1 Year Ago	-0.0685 ***	-0.0058
	(0.0102)	(0.0057)
1-2 Years Ago	-0.1086 ***	-0.0073
	(0.0099)	(0.0049)
2+ Years Ago	-0.0601 ***	0.0160 ***
	(0.0102)	(0.0048)
Own Exogenous Health Shock of Female Worker:		
0-1 Year Ago	-0.2536 **	-0.0459
	(0.0971)	(0.0726)
1-2 Years Ago	-0.0957	-0.0357
	(0.1169)	(0.0680)
2+ Years Ago	-0.0569	0.0564
	(0.1559)	(0.1368)
Own Exogenous Layoff Shock of Female Worker:		
0-1 Year Ago	-0.0952 ***	0.0389 **
	(0.0168)	(0.0135)
1-2 Years Ago	-0.0599 ***	0.0166
	(0.0171)	(0.0130)
2+ Years Ago	-0.0443 *	0.0532 ***
	(0.0173)	(0.0133)
Stdev. Residuals: $\sigma_\epsilon, \sigma_\eta$	0.3105	0.1694
Stdev. Person Effects: $\sigma_\theta, \sigma_\alpha$	0.3219	0.2156
Corr. Person Effects: $\rho_{\theta,\alpha}$	0.5005	
Stdev. Job Match Effects: σ_ψ, σ_χ	0.3486	0.3888
Corr. Job Match Effects: $\rho_{\psi,\chi}$	0.2338	
Number of Workers	6,225	
Number of Jobs	10,120	
ln-L	-27,668.66	

Note: Asymptotic standard errors are in parentheses. Significance: '*'=5%; '**'=1%; '***'=0.1%.

Table 1.33: Percent Effect of Own Exogenous Health and Layoff Shocks on the Hourly Wage and Weekly Hours of Married Workers in the Unrestricted Sample-Significant Values Only (SIPP Health Measures)

	SIPP Health Measures	
	Hourly Wage	**Weekly Hours**
Own Exogenous Health Shock of Male Worker:		
0-1 Year Ago	-0.2356	-0.0766
1-2 Years Ago	-0.1513	-0.0504
2+ Years Ago	-0.1526	-0.0736
Own Exogenous Layoff Shock of Male Worker:		
0-1 Year Ago	-0.0591	-
1-2 Years Ago	-0.0974	-
2+ Years Ago	-0.0422	0.0189
Own Exogenous Health Shock of Female Worker:		
0-1 Year Ago	-0.1838	-0.0924
1-2 Years Ago	-0.1110	-0.0336
2+ Years Ago	-0.1059	0.0720
Own Exogenous Layoff Shock of Female Worker:		
0-1 Year Ago	-0.0843	0.0374
1-2 Years Ago	-0.0480	-
2+ Years Ago	-	0.0598

Note: The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: e^{δ}-1.

1.6 Conclusion

This study has addressed the manner in which the impacts of displacements originating from layoff or disability continue to affect employees in the years subsequent to their reemployment. Convincing evidence of the lasting shifts in the wage rates and hours of those shocked out of employment has been presented in this paper, further contributing to the existing research on worker dislocations.

Relative to the full population of employed individuals, high attachment workers generally have more moderate shifts in their economic outcomes in the years following exogenous exits. While both types of negative shocks place workers on an initially lower wage trajectory, the consequences dissipate over the adjustment period. Scars from displacement have the most lasting impact on the disabled,

Table 1.34: Percent Effect of Own Exogenous Health and Layoff Shocks on the Hourly Wage and Weekly Hours of Married Workers in the Restricted Sample- Significant Values Only (SSA Health Measures)

	SIPP Health Measures		**SSA Health Measures**	
	Hourly Wage	**Weekly Hours**	**Hourly Wage**	**Weekly Hours**
Own Exogenous Health Shock of Male Worker:				
0-1 Year Ago	-0.2203	-0.0917	-0.1837	-
1-2 Years Ago	-0.1641	-0.0391	-0.1188	-
2+ Years Ago	-0.1590	-0.0648	-0.2882	-
Own Exogenous Layoff Shock of Male Worker:				
0-1 Year Ago	-0.0642	-	-0.0662	-
1-2 Years Ago	-0.1012	-	-0.1029	-
2+ Years Ago	-0.0574	0.0164	-0.0583	0.0161
Own Exogenous Health Shock of Female Worker:				
0-1 Year Ago	-0.1856	-	-0.2240	-
1-2 Years Ago	-0.0821	-	-	-
2+ Years Ago	-0.0897	0.0575	-	-
Own Exogenous Layoff Shock of Female Worker:				
0-1 Year Ago	-0.0924	0.0390	-0.0908	0.0397
1-2 Years Ago	-0.0588	0.0163	-0.0581	-
2+ Years Ago	-0.0440	0.0543	-0.0433	0.0546

Note: The percent effect on the hourly wage and weekly hours of a worker is calculated by exponentiating the estimated coefficient of interest and subtracting one from this value: e^{δ}-1.

plaguing their future work histories to a greater extent. Both the wages and hours of this population are negatively impacted following an unanticipated exit from the work force. Those who return to work after experiencing a layoff spend an increased amount of time at their jobs and are able to recover much of their initial earnings losses with each successive year that passes.

Curiously, those located at the bottom of the educational hierarchy are not the ones whose wages suffer most from employment shocks. The better educated are in fact worse off monetarily following displacing events as compared to those with only a high school diploma regardless of the source of the exit. The disparity by education is most pronounced in the years after an episode of ill health: as compared to employees with an increased taste for learning, those with less schooling work fewer hours each year while earning wage rates that are larger. These differences may be caused by the severity of the impairments that induce job exits for those with more than a high school diploma along with lost specific human capital.

In the gender analysis, I find that men have persistent depressed wage rates, whereas women initially experience more substantial monetary losses but are able to recover by the end of the third year after a layoff. The genders behave uniquely in terms of the time they spend at work after this type of dislocation: women immediately demonstrate large improvements in weekly hours, whereas men only begin to work more than those with continuous employment in the third year after the exit. The magnitude of the detrimental impact of a health shock is most extremely manifested for males in both economic measures.

Estimates from the specification analyzing the role of race make it difficult to draw concrete conclusions about the comparative behaviors of whites and non-whites. This is because of the variance in the degree of the lingering impacts of displacements over time. Following a layoff, whites consistently spend slightly more time at work, whereas it is generally true that nonwhites do not have weekly hours that significantly differ from those with continuous employment. An event of poor health has greater and more persistent negative impacts for whites in both their wages and supply of labor.

Uncovered by the spousal analyses is an awareness that those with partners who exit their positions due to an unanticipated shock are unambiguously affected by these events. Women with husbands who have been laid off become more attached to their positions as compared to the baseline married employee after at least two years. Health shocks induce working spouses to also transition out of employment in the year of the displacement. For men, this behavior continues into the second year, while wives in the next few years are the inclined to remain with their employer. Shifting health insurance coverage to the unaffected spouse may be the motivation for some of these outcomes. Layoffs of husbands have a positive effect on women's weekly hours, whereas men do not alter their hours when their wives have been displaced. However, in the case of a health shock, men and women similarly become less present at work by decreasing their hours relative to workers without spouses who have experienced an impairment. The response of females to the illnesses of their husbands is more extreme as manifested in their hours at work than is their behavior following their own personal job separations.

Results found using measures of limiting health conditions in survey data sets mirror those found using administrative indicators of disability within a margin of error. The accuracy of the data routinely collected in household surveys do appear to give reasonable results as defined by the signs and orders of magnitude of the impacts as time progresses since the date of the event. The trends exhibited do not appear to substantially differ from benefits data, although it is clear that administrative sources capture more severe traumas. The benefits records provide informative clues about the shortcomings of survey measures of work-limiting impairments: they cannot discriminate between transient and chronic conditions that continuously plague a worker the same way that medical records can.

This study suggests the need for additional investigations into the struggles of workers who become reemployed after recovering from a serious illness. Only by continuing to extend the techniques established by researchers of firm-induced displacements to include examinations of those who separated from their jobs because of medical disability will sufficient knowledge of their plight be uncovered. It will be particularly important to capture the role that transitioning to positions in different industries and occupations plays in mitigating the impacts of these dislocations in future work. Furthermore, it will be revealing to explore crossovers between these populations, as the propensity of laid off workers with minor ailments to apply for Social Security Disability Insurance in lieu of immediately searching for new job matches remains unaddressed.

Chapter 2

Linking Human Capital to Productivity in the U.S. Economy

2.1 Introduction

With the advent of innovative econometric techniques coupled with the increasing availability of longitudinally-integrated employer-employee data, it has recently become possible to explore the measure of productivity with more detailed analyses. Jorgenson, Gollop, and Fraumeni (1987) spent many years estimating the impact that changes in the composition of the labor force have upon productivity. Researchers at the Bureau of Labor Statistics followed suit by designing a methodology that is consistent with the procedure introduced by Jorgenson, Gollop, and Fraumeni and that allows for worker heterogeneity by modeling the differences in the marginal products of workers (U. S. Department of Labor and Bureau of Labor Statistics 1993, and Dean and Harper 1998). Abowd, Lengermann, and McKinney (2002) have contributed to the studies of labor productivity by considering a measure of human capital derived from estimates of a wage equation that includes both fixed person and firm effects. This method allows for more within and across firm heterogeneity.

As part of a joint Bureau of Labor Statistics and Bureau of the Census project, we desire to examine measures of productivity produced by methods developed at the Longitudinal Employer-Household Dynamics Program that can be compared with those derived from multifactor productivity models of the BLS that are based upon the methods of Jorgenson, Gollop, and Fraumeni. In doing so, we hope to provide an additional estimate of the effects of labor composition on productivity by using recently integrated data. This work will explore measures of human capital that are linked to indicators of productivity in multiple states from 1990-2002.

We begin with a review of the theory that describes the development of the index of labor composition as outlined by Jorgenson, Gollop, and Fraumeni. This index requires knowledge of total labor volume and hours, as well as a price of labor. In order to define this constant quality price index of labor, we subsequently present our wage model, which focuses on the role of human capital and is based upon the works of Becker (1964), Mincer (1974) and Abowd, Kramarz, and Margolis (1999). Estimates from this fixed effects model are incorporated into the creation of two separate price indices: one that is consistent with the Bureau of Labor Statistics' methods, and a second Census-proposed alternative measure that is based upon human capital. Cells of classification remain the same between the BLS and Census-proposed alternative indices, with each using categories defined by education groups and years of experience.[1] Tables of the two indices of the composition of the labor force are presented by gender and industry sectors for each year, and results are summarized.

2.2 Labor Composition

To explore the manner in which changes in labor composition affect measures of productivity, we first review the labor composition model. Jorgenson, Gollop, and Fraumeni (1987) and Ho and Jorgenson (1999) present the theory behind this

[1] Both analyses examine the changing composition of the labor force separately by gender and industry division.

model, which was adopted by the Bureau of Labor Statistics.

We begin by assuming a translog production function in which the quantity of output or value added, Q, is generated by aggregated capital inputs, K, m types of labor inputs,$\{l_k\}_{k=1}^{m}$, and the technology available at time t, A_t:

$$Q = A_t * g(K, l_1, ..., l_m). \tag{2.1}$$

The labor inputs, l_k, can be thought of as hours of work that have been disaggregated by the characteristics, k, of individual workers. This representation accounts for the heterogeneity of the labor force, as the productive value of an hour likely varies depending on the level of education, experience, and skill that a worker has acquired.

Taking the logarithm and then the derivative with respect to time of the translog production function, we express it in terms of growth rates as

$$\frac{\dot{Q}}{Q} = \frac{\dot{A}}{A} + \frac{\partial Q}{\partial K}\frac{\dot{K}}{K} + \sum_{k=1}^{m} \frac{\partial Q}{\partial l_k}\frac{\dot{l}_k}{l_k}. \tag{2.2}$$

We see from this equation that the growth rate of output, $\frac{\dot{Q}}{Q}$, depends on the growth rate of aggregate capital services, $\frac{\dot{K}}{K}$, the growth rates of the m types of labor services, $\left\{\frac{\dot{l}_k}{l_k}\right\}_{k=1}^{m}$, and the growth rate of multifactor productivity, $\frac{\dot{A}}{A}$. Distinguishing between the substitution of inputs and the growth rate of productivity, weighed by their marginal products, is necessary in defining an appropriate measure of labor quality.

We assume that the production function exhibits constant returns to scale and that factor input markets are in competitive equilibrium. We further assume cost minimizing behavior, so that the output elasticity of each factor equals its share of total costs. The factor cost shares of capital and labor are respectively given by

$$s_C = \frac{p_C K}{p_C K + \sum_k p_{lk} l_k} \tag{2.3}$$

$$s_{lk} = \frac{p_{lk} l_k}{p_C K + \sum_k p_{lk} l_k}, \tag{2.4}$$

where p_C and p_{lk} are the prices of capital and labor services for the k^{th} type of labor. K is the total quantity of capital and $l_k = \sum_{i \in k} R_i$ represents the k^{th} quantity of hours for the corresponding labor services. The index of the price of labor inputs, normalized to one in 2000, is the value of labor compensation divided by the volume index:

$$P_L = \frac{\sum_k p_{lk} l_k}{R}.$$

Rearranging (2.2), we see that the growth rate of multifactor productivity can alternatively be written as

$$\frac{\dot{A}}{A} = \frac{\dot{Q}}{Q} - s_C \frac{\dot{K}}{K} - \sum_{k=1}^{m} s_{lk} \frac{\dot{l}_k}{l_k}. \tag{2.5}$$

Additional assumptions of separability of inputs and Hicks neutral technical change allow us to focus on aggregates of labor input as

$$\frac{\dot{L}}{L} = \sum_{k=1}^{m} s_{Lk} \frac{\dot{l}_k}{l_k}, \tag{2.6}$$

where

$$s_{Lk} = \frac{s_{lk}}{s_L} = \frac{p_{lk} l_k}{\sum_k p_{lk} l_k}. \tag{2.7}$$

We express the aggregate form of (2.5) as

$$\frac{\dot{A}}{A} = \frac{\dot{Q}}{Q} - s_C \frac{\dot{K}}{K} - s_L \frac{\dot{L}}{L}, \tag{2.8}$$

where the shares of total costs for capital and labor are s_C and s_L.

Following Jorgenson, Gollop, and Fraumeni, we assume that a constant of proportionality we term the composition of the labor force, LC, transforms hours worked, R, into flows of labor services, L:

$$L = LC \times R.$$

Thus, the growth rate of labor inputs is the sum of the growth rate of total hours and labor composition:

$$\frac{\dot{L}}{L} = \frac{\dot{LC}}{LC} + \frac{\dot{R}}{R}. \tag{2.9}$$

Given our assumptions, the instantaneous growth rates can be replaced by annual rates of change. The Tornqvist index number formula measures these as differences in successive logarithms. Equation (2.9) informs us that the growth rate of total hours and labor composition together sum to equal the growth rate of labor inputs. Changes in the index of labor composition, LC, are thus defined as the difference between changes in the aggregate labor input index, L, and the unweighted sum of the hours of all persons, R.

$$\triangle \ln LC = \triangle \ln L - \triangle \ln R = \triangle \ln \left(\frac{L}{R}\right), \tag{2.10}$$

where from (2.6) we know

$$\triangle \ln L = \sum_{k=1}^{m} \frac{1}{2} \left[s_{Lk}(t) + s_{Lk}(t-1)\right] \triangle \ln l_k. \tag{2.11}$$

Letting k denote the cross-classified worker types, the index of sectoral labor input, L, can be expressed as a translog function of its individual components of hours, l_k. This Tornqvist index of sectoral volume is represented by a translog constant quantity index of the individual labor inputs:

$$\triangle \ln L = \sum_{k} \bar{s}_{Lk} \triangle \ln l_k. \tag{2.12}$$

The weights in (2.12) are given for each industry division by the average value share of each component, which are

$$\bar{s}_{Lk} = \frac{1}{2} \left[s_{Lk}(t) + s_{Lk}(t-1)\right], \tag{2.13}$$

These value shares are derived from data on labor compensation that are cross-classified by cell values as described by equation (2.7). An index number time series is retrieved by chaining the logarithmic differences given by (2.12) and by using the exponential function.

The changes in the index of labor composition are represented by uniting equations (2.10) and (2.12), which yields

$$\triangle \ln LC = \sum_{k=1}^{m} \bar{s}_{Lk} \triangle \ln l_k - \triangle \ln R, \tag{2.14}$$

where $R = \sum_k l_k$, since l_k is the aggregate level of annual hours for each cell k. From this equation, we see that labor quality is the ratio of labor volume (the constant quality index) to hours worked, or the weighted and unweighted growth rates of hours. This equation can be used equally well to measure both aggregate and sectoral labor quality.

2.3 Wage Model

The Bureau of Labor Statistics implements a wage model to derive labor market prices for cross-classified worker types rather than utilizing average earnings data. Estimates of the prices of each relevant type of labor using the BLS methodology are obtained from coefficients from annually-fitted hourly earnings functions. The wage functions are separately estimated for men and women using categories for seven education groups and seventy-two levels of work experience, yielding 1,008 cells.

We propose exploring the changing composition of the labor force by expanding the wage model originally conceived by the BLS to explore a new measure of the price of labor. We do so by placing our focus on the role of human capital, or skill. The seminal works of Becker and Mincer define H_{it} to be individual i's stock of general human capital in time period t, which is assumed to be fully transferrable as a worker moves among jobs in a given labor market, f. A worker's full-time full-year wage rate is defined within this labor market as

$$w_{it} = r_{ft} H_{it}, \tag{2.15}$$

where the rental rate of human capital is r_{ft}. The production function

$$H_{it} = e^{\theta_i + X_{it}'^{\exp} \beta^{\exp} + \ln(50 \times 35)} \tag{2.16}$$

assumes that labor force experience, $X_{it}^{\exp}$, a person-specific component, θ_i, and the logarithm of annual full-year, full-time hours[2] are the inputs required for the generation of human capital.

Uniting equations (2.15) and (2.16) and taking the logarithm yields

$$\ln w_{it} = \ln r_{ft} + \theta_i + X_{it}'^{\exp} \beta^{\exp} + \ln(50 \times 35). \tag{2.17}$$

The full-time, full-year log wage rate, or full human capital, is the earnings a worker would receive if that person worked exactly 50×35 hours in the year. This derivation of the standard human capital log wage function permits us to interpret the time and location effects as log prices. We also see that the logarithm of an individual's human capital stock is

$$\ln H_{it} = h_{it} = \theta_i + X_{it}'^{\exp} \beta^{\exp} + \ln(50 \times 35), \tag{2.18}$$

and the wage function is

$$w = w(h_{it}, r_{ft}). \tag{2.19}$$

Note that (2.19) holds true within a competitive labor market that has no firm-level wage heterogeneity. It is this formulation that will be used to construct our index of human capital.

[2] Full-time, full-year employees work 35 hours or more each week and 50 or more hours each year.

Following the 1999 article of Abowd, Kramarz, and Margolis, we detail a methodology in which an employee's wage rate can be decomposed into parts that, in addition to observable characteristics, include both unmeasured person and firm fixed effects. More explicitly, for each individual, i, and firm, j, in time period t, we define

$$\ln w_{ijt} = X_{it}'\beta + \theta_i + \psi_j + \varepsilon_{ijt}, \tag{2.20}$$

where the log wage rate, $\ln w_{ijt}$, is the natural logarithm of the real annualized wage at the dominant firm, $X_{it}'\beta$ is the effect of time-varying characteristics, θ_i is the person fixed effect, ψ_j is the fixed firm effect, and ε_{ijt} is the statistical residual. The covariates are interacted with sex and include the following: experience quartic, aggregate earnings; unemployment rate; full quarter, continuous quarter, and raw quarter dummies; the logarithm of annual hours worked at dominant job; age 66-75 and age 76-85 dummies; Heckit variables to capture selection into and out of the sample; and left and right edge dummy variables for when data is missing on a boundary quarter.

From this estimation, the individual effect can be further decomposed into observable and unobservable parts that do not time-vary in the following manner:

$$\theta_i = \alpha_i + u_i^{'}\eta_i. \tag{2.21}$$

This is how we acquire coefficient estimates for a male indicator variable, as well as for the education groups for each gender. Similarly, the fixed firm effect can be decomposed by

$$\psi_j = \upsilon_j + \mu_j^{'}\nu_j \tag{2.22}$$

to yield coefficient estimates for Census Division and Metropolitan Statistical Area for the place of work.

Abowd, Lengermann, and McKinney (2002) implement an estimation similar to (2.20) separately for each state. We instead estimate this equation for all states at once. We interpret human capital, or skill as defined by (2.18), which consists of the person fixed effect, θ_i and the experience component of $X'_{it}\beta$ from the estimation of (2.20) above evaluated at full-year full-time hours.

2.4 The Price of Labor

2.4.1 Adapted Bureau of Labor Statistics Price of Labor

We follow the Bureau of Labor Statistics' methodology by estimating a wage equation (2.20). Doing so does not confound person and firm heterogeneity in the index of labor quality, as would be the case if the price of labor were defined by using compensation directly. The Jorgenson price of the full-time hourly wage rate for each worker type is assigned based on an adaptation of the BLS price equation:

$$p_{lkt} = a_t^{'} + X_{kt}^{\prime \exp}\beta^{\exp} + u_{kt}^{\prime educ}\eta_i^{educ} + (\gamma - 1)\ln(50 \times 35), \tag{2.23}$$

where

$$a_t^{'} = a + \bar{Z}_t^{\prime}\varsigma.$$

We make an adjustment so that the price of labor is not for annual earnings, but rather is for the hourly wage rate for a full-time job holder by including the term $(\gamma - 1)\ln(50 \times 35)$ on the right hand side of (2.23).[3] It is this equation that is utilized in the computation of the traditional Bureau of Labor Statistics indices of labor productivity by 1,008 cells, k, of education, work experience, and sex. It is normalized to one in 2000 for ease of interpretation.

[3] The coefficient on the logarithm of annual hours worked, γ, is derived from the estimation of the wage equation (2.20).

The intercept, a_t', can be interpreted as the return to all characteristics other than education and experience, since it is an average for all persons of the same sex. We extract from the estimation of our model using equation (2.22) the coefficients for time-varying place of work geography,[4] ν_j. The Census Division of place of work and an indicator of whether employment is inside a Metropolitan Statistical Area define the geography variables. In addition to the weighted averages of the time-varying geography characteristics, $\bar{\mu}_t'$, aggregate yearly earnings and the yearly unemployment rate contribute to our overall measure of $\bar{Z}_t'$, with the returns to these characteristics for each gender incorporated into a_t'.

Equation (2.21) is used to decompose the fixed person effect, θ_i, into a male indicator variable and categories schooling[5] to derive the education coefficients, η_i^{educ}, for each gender. The experience component and its square from our estimation of (2.20), $X_{kt}'^{\exp}\beta^{\exp}$ is also incorporated into (2.23).

2.4.2 Census-Proposed Alternative Price of Labor

We use the nationally-weighted aggregate value of human capital[6] from the estimation of (2.20) in our alternative Beckerian price of labor. This enables us to characterize differences within and between the industry divisions we are studying by the level of human capital. We allow the price of labor in each period to be defined within 1,008 cells, k, of experience, education, and gender as an implicit

[4]This differs from the original methodology of the Bureau of Labor Statistics, which uses place of residence in defining the geography variables. Veteran status is not controlled for, nor is part-time work.

[5]The education groups we use are 0-8, 9-11, 12, 13-15, 16, and 17 or more years of schooling.

[6]Since the Census data base does not as of yet consist of the universe of states, we utilize national weights derived from industry and demographic control totals in deriving these distributions.

wage. We adapt the method of Lengermann (2002), defining average industry human capital as the price of labor:

$$p_{lkt} = \frac{\sum_{i \in k} h_{it}}{l_{kt}}, \tag{2.24}$$

Unlike Lengermann, who divides by total employment, we use a denominator of total hours for each cell k, $l_{kt} = \sum_{i \in k} R_{it}$. Using human capital in this manner provides us with a time-invariant implicit wage.

A key distinction between the Jorgenson and Beckerian prices is that Beckerian prices are based upon equation (2.15). This equation equates the wage rate, w_{it}, as the product of human capital, H_{it}, and its rental rate, r_{ft}. Jorgenson prices, however, are based upon concepts that relate specifically to the returns to education and experience.

2.5 Results

Tables 2.1-2.8 present the constant quality price index of labor (p_l) and the constant quality index of labor ($\triangle \ln L$) for males and females following the Bureau of Labor Statistics and the Census-proposed alternative methodologies. Price has been normalized to unity in 2000 to permit the ease of interpretation across methods. Recall that the price index is defined by the BLS based upon returns to characteristics described by an estimated wage equation. The Census-proposed alternative measure instead incorporates aggregate human capital into the price of labor. For each industry division, gender, and year spanning 1990-2002, Tables 2.9 and 2.10 summarize total annual hours (R).

On average for men in all sectors, the volume of total annual hours decreased between 1990 and 2002 by 5.79%. During this same timeframe, women experienced

Table 2.1: Bureau of Labor Statistics' Method (TFP) Constant Quality Price Index of Labor for Males

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	0.9941	1.0065	1.0015	0.9988	0.9923	1.0034	1.0041
Construction	0.9930	0.9953	0.9925	0.9920	0.9906	0.9908	0.9910
Trans. & Utilities	1.0086	1.0041	1.0005	1.0014	0.9974	0.9972	0.9958
Wholesale Trade	1.0008	1.0041	1.0040	1.0041	1.0012	1.0004	0.9993
Retail Trade	0.9938	0.9982	0.9987	0.9994	0.9980	0.9985	0.9988
FIRE	0.9951	0.9916	0.9905	0.9928	0.9887	0.9854	0.9888
Services	0.9927	0.9916	0.9903	0.9900	0.9889	0.9896	0.9908
Durable Manufacturing	1.0046	1.0016	0.9978	0.9997	0.9983	1.0015	0.9999
Nondurable Manufacturing	1.0094	1.0063	1.0027	1.0048	1.0023	1.0038	0.9990

Industry	1997	1998	1999	2000	2001	2002
Mining	1.0040	1.0039	0.9951	1.0000	1.0048	0.9911
Construction	0.9914	0.9952	0.9977	1.0000	0.9971	0.9944
Trans. & Utilities	0.9955	0.9990	0.9981	1.0000	0.9961	0.9862
Wholesale Trade	0.9993	1.0027	1.0006	1.0000	0.9942	0.9866
Retail Trade	0.9985	1.0000	0.9997	1.0000	0.9969	0.9952
FIRE	0.9912	0.9985	1.0007	1.0000	0.9977	0.9939
Services	0.9917	0.9962	0.9983	1.0000	0.9971	0.9929
Durable Manufacturing	0.9995	1.0023	1.0002	1.0000	0.9935	0.9825
Nondurable Manufacturing	0.9979	1.0006	0.9998	1.0000	0.9944	0.9879

Table 2.2: Bureau of Labor Statistics' Method (TFP) Constant Quality Price Index of Labor for Females

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	1.0346	1.0380	1.0332	1.0251	1.0163	1.0205	1.0173
Construction	1.0025	1.0048	1.0017	0.9977	0.9932	0.9937	0.9947
Trans. & Utilities	1.0165	1.0159	1.0146	1.0100	1.0034	1.0036	1.0018
Wholesale Trade	1.0110	1.0145	1.0155	1.0105	1.0056	1.0057	1.0034
Retail Trade	1.0057	1.0084	1.0083	1.0060	1.0022	1.0026	1.0025
FIRE	1.0283	1.0292	1.0277	1.0246	1.0160	1.0109	1.0096
Services	1.0112	1.0136	1.0101	1.0073	1.0026	1.0021	1.0023
Durable Manufacturing	1.0199	1.0224	1.0188	1.0134	1.0066	1.0082	1.0045
Nondurable Manufacturing	1.0173	1.0138	1.0088	1.0042	0.9998	1.0021	0.9990

Industry	1997	1998	1999	2000	2001	2002
Mining	1.0123	1.0113	1.0037	1.0000	0.9977	0.9882
Construction	0.9933	0.9953	0.9996	1.0000	1.0004	0.9952
Trans. & Utilities	0.9988	0.9999	1.0005	1.0000	0.9967	0.9846
Wholesale Trade	1.0001	1.0015	1.0016	1.0000	0.9962	0.9862
Retail Trade	1.0006	1.0012	1.0022	1.0000	0.9984	0.9956
FIRE	1.0055	1.0067	1.0060	1.0000	0.9959	0.9847
Services	1.0000	1.0009	1.0021	1.0000	0.9973	0.9899
Durable Manufacturing	1.0008	1.0021	1.0017	1.0000	0.9946	0.9813
Nondurable Manufacturing	0.9951	0.9987	1.0009	1.0000	0.9967	0.9898

Table 2.3: Census-Proposed Alternative Constant Quality Price Index of Labor for Males

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	0.8028	0.7873	0.8297	0.8805	0.8744	0.9358	0.9519
Construction	0.9614	0.9450	0.9563	0.9743	1.0054	1.0067	1.0030
Trans. & Utilities	0.9291	0.9227	0.9122	0.9327	0.9588	0.9783	0.9811
Wholesale Trade	0.9973	0.9771	0.9381	0.9556	0.9717	0.9793	0.9750
Retail Trade	0.9857	0.9738	0.8998	0.9267	0.9560	0.9808	0.9677
FIRE	1.0026	0.9740	0.9658	0.9941	0.9990	1.0044	1.0205
Services	0.9285	0.9235	0.9364	0.9625	0.9891	1.0094	0.9979
Durable Manufacturing	0.9151	0.9101	0.9076	0.9349	0.9696	0.9722	0.9708
Nondurable Manufacturing	0.8918	0.8851	0.9105	0.9341	0.9609	0.9684	0.9676

Industry	1997	1998	1999	2000	2001	2002
Mining	0.9695	0.9486	0.9572	1.0000	0.9812	0.9409
Construction	1.0210	1.0125	1.0105	1.0000	0.9743	0.9506
Trans. & Utilities	0.9965	0.9831	0.9940	1.0000	0.9637	0.9424
Wholesale Trade	0.9969	0.9882	0.9931	1.0000	0.9602	0.9483
Retail Trade	0.9816	0.9664	0.9630	1.0000	0.9611	0.9079
FIRE	1.0241	1.0191	1.0031	1.0000	0.9645	0.9483
Services	1.0145	1.0087	1.0131	1.0000	0.9556	0.9271
Durable Manufacturing	0.9907	0.9750	0.9928	1.0000	0.9648	0.9521
Nondurable Manufacturing	0.9874	0.9780	1.0008	1.0000	0.9702	0.9537

Table 2.4: Census-Proposed Alternative Constant Quality Price Index of Labor for Females

Industry	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**
Mining	1.3747	0.9894	0.9462	0.9564	0.9451	0.9118	0.9330
Construction	1.0342	1.0019	0.9792	0.9606	0.9680	0.9811	0.9904
Trans. & Utilities	0.9342	0.9233	0.8963	0.9138	0.9394	0.9646	0.9798
Wholesale Trade	1.0119	1.0015	0.9531	0.9702	0.9872	1.0110	1.0040
Retail Trade	1.0832	1.0581	0.9464	0.9527	0.9736	1.0073	0.9998
FIRE	1.0456	1.0169	0.9773	0.9845	0.9867	1.0050	1.0297
Services	1.0194	0.9840	0.9707	0.9809	0.9923	1.0216	1.0193
Durable Manufacturing	0.8955	0.8910	0.8887	0.9124	0.9520	0.9555	0.9637
Nondurable Manufacturing	0.9068	0.9012	0.9369	0.9627	0.9856	0.9921	0.9936

Industry	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
Mining	0.9591	0.9584	0.9689	1.0000	0.9688	0.9395
Construction	1.0050	0.9895	0.9954	1.0000	0.9772	0.9396
Trans. & Utilities	0.9942	0.9813	0.9946	1.0000	0.9561	0.9308
Wholesale Trade	1.0129	0.9966	1.0000	1.0000	0.9660	0.9429
Retail Trade	1.0019	0.9812	0.9840	1.0000	0.9590	0.9078
FIRE	1.0381	1.0212	1.0099	1.0000	0.9662	0.9400
Services	1.0282	1.0097	1.0139	1.0000	0.9523	0.9139
Durable Manufacturing	0.9814	0.9679	0.9833	1.0000	0.9572	0.9442
Nondurable Manufacturing	1.0132	0.9931	0.9978	1.0000	0.9581	0.9411

Table 2.5: Bureau of Labor Statistics' Method Constant Quality Index of Labor for Males (in Millions)

Industry	1990	1991	1992	1993	1994
Mining	9,985	9,605	8,050	7,438	6,950
Construction	17,924	15,785	14,965	14,990	15,633
Trans. & Utilities	76,042	75,263	72,262	72,530	72,243
Wholesale Trade	41,444	39,900	39,861	39,458	39,854
Retail Trade	96,096	92,944	101,464	104,387	105,422
FIRE	18,259	17,248	16,978	17,302	17,128
Services	153,393	144,583	152,223	157,521	157,617
Durable Manufacturing	152,274	142,299	134,014	132,833	134,053
Nondurable Manufacturing	66,284	59,093	57,263	58,359	57,126

Industry	1995	1996	1997	1998	1999
Mining	6,156	6,129	6,449	6,152	5,514
Construction	15,478	15,828	16,811	17,185	17,851
Trans. & Utilities	73,399	72,855	76,524	76,223	79,070
Wholesale Trade	40,794	40,700	42,206	42,193	42,405
Retail Trade	107,557	108,657	113,779	113,767	116,149
FIRE	16,843	17,244	18,241	18,520	18,963
Services	164,308	170,025	179,355	182,400	190,292
Durable Manufacturing	135,740	134,853	139,154	139,164	136,508
Nondurable Manufacturing	57,043	55,115	55,262	53,955	52,628

Industry	2000	2001	2002
Mining	5,542	5,877	5,475
Construction	18,609	18,430	17,924
Trans. & Utilities	81,108	80,730	77,175
Wholesale Trade	42,680	40,923	39,902
Retail Trade	117,371	118,787	120,232
FIRE	19,015	19,265	19,588
Services	203,576	199,483	199,314
Durable Manufacturing	136,461	128,461	120,198
Nondurable Manufacturing	51,894	48,932	48,175

Table 2.6: Bureau of Labor Statistics' Method Constant Quality Index of Labor for Females (in Millions)

Industry	**1990**	**1991**	**1992**	**1993**	**1994**
Mining	612	733	754	705	717
Construction	2,012	1,413	1,506	1,625	1,845
Trans. & Utilities	23,789	21,063	22,027	22,333	23,248
Wholesale Trade	45,605	39,559	42,491	41,357	43,495
Retail Trade	67,569	63,915	67,652	68,471	71,950
FIRE	18,360	17,772	18,543	18,687	18,873
Services	192,504	185,556	189,469	192,857	201,718
Durable Manufacturing	50,134	43,071	43,770	42,229	43,546
Nondurable Manufacturing	37,135	37,293	35,651	34,372	34,275

Industry	**1995**	**1996**	**1997**	**1998**	**1999**
Mining	919	871	840	804	747
Construction	1,840	1,896	2,071	2,141	2,342
Trans. & Utilities	23,796	23,772	25,312	25,194	26,287
Wholesale Trade	43,321	43,642	45,880	45,819	45,875
Retail Trade	73,321	74,004	78,434	79,735	81,371
FIRE	18,322	18,177	19,588	20,064	20,288
Services	210,643	218,237	233,806	240,634	248,657
Durable Manufacturing	43,569	43,210	44,574	44,266	43,942
Nondurable Manufacturing	32,912	31,364	31,292	30,455	29,634

Industry	**2000**	**2001**	**2002**
Mining	782	759	745
Construction	2,501	2,504	2,432
Trans. & Utilities	27,277	26,958	24,489
Wholesale Trade	46,523	43,817	41,828
Retail Trade	82,430	82,501	82,165
FIRE	20,203	20,389	20,120
Services	261,471	261,627	259,276
Durable Manufacturing	44,198	40,916	35,977
Nondurable Manufacturing	28,833	26,984	25,381

Table 2.7: Census-Proposed Alternative Constant Quality Index of Labor for Males (in 10,000s)

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	1,102	1,052	922	867	828	751	749
Construction	11,018	9,731	9,298	9,298	9,772	9,749	10,011
Trans. & Utilities	7,311	7,209	6,797	6,791	6,768	6,885	6,850
Wholesale Trade	7,218	6,884	6,645	6,533	6,578	6,742	6,754
Retail Trade	19,568	18,684	19,704	20,204	20,366	20,847	20,933
FIRE	4,279	4,032	3,920	4,014	3,969	3,907	3,996
Services	18,188	17,236	18,564	19,248	19,353	20,177	20,877
Durable Manufacturing	12,087	11,260	10,596	10,489	10,616	10,762	10,715
Nondurable Manufacturing	7,629	6,821	6,705	6,844	6,732	6,741	6,558

Industry	1997	1998	1999	2000	2001	2002
Mining	789	761	701	706	744	710
Construction	10,718	10,986	11,466	11,976	11,869	11,646
Trans. & Utilities	7,240	7,207	7,510	7,745	7,713	7,454
Wholesale Trade	7,043	7,056	7,148	7,222	6,949	6,865
Retail Trade	22,036	21,851	22,182	23,058	23,258	23,399
FIRE	4,251	4,331	4,437	4,491	4,546	4,645
Services	22,234	22,664	23,794	25,430	25,050	25,058
Durable Manufacturing	11,145	11,167	11,021	11,090	10,482	9,906
Nondurable Manufacturing	6,627	6,497	6,385	6,327	5,997	5,932

Table 2.8: Census-Proposed Alternative Constant Quality Index of Labor for Females (in 10,000s)

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	99	117	117	110	112	143	137
Construction	1,608	1,125	1,177	1,268	1,439	1,441	1,490
Trans. & Utilities	2,950	2,601	2,684	2,718	2,834	2,904	2,912
Wholesale Trade	3,257	2,838	2,992	2,924	3,083	3,106	3,145
Retail Trade	22,128	20,595	20,614	20,497	21,414	21,974	22,009
FIRE	6,323	6,069	6,111	6,104	6,150	5,992	5,960
Services	22,556	21,575	22,191	22,515	23,505	24,447	25,361
Durable Manufacturing	4,446	3,816	3,947	3,846	4,004	4,013	4,012
Nondurable Manufacturing	4,899	4,898	4,886	4,792	4,816	4,607	4,426

Industry	1997	1998	1999	2000	2001	2002
Mining	134	130	122	128	126	125
Construction	1,640	1,686	1,847	1,978	1,978	1,932
Trans. & Utilities	3,126	3,119	3,268	3,405	3,375	3,102
Wholesale Trade	3,328	3,332	3,368	3,430	3,263	3,154
Retail Trade	23,406	23,540	24,003	24,534	24,381	24,135
FIRE	6,476	6,619	6,729	6,739	6,816	6,774
Services	27,367	28,060	29,097	30,644	30,604	30,417
Durable Manufacturing	4,182	4,172	4,158	4,214	3,925	3,517
Nondurable Manufacturing	4,492	4,372	4,262	4,161	3,899	3,716

Table 2.9: Industry Labor Input of Total Annual Hours for Males (in Millions)

Industry	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**
Mining	1,166	1,110	951	884	833	737	735
Construction	2,011	1,782	1,701	1,704	1,782	1,769	1,814
Trans. & Utilities	9,070	9,024	8,728	8,748	8,754	8,922	8,894
Wholesale Trade	4,929	4,736	4,743	4,692	4,756	4,888	4,895
Retail Trade	11,406	10,996	12,078	12,415	12,564	12,851	13,014
FIRE	2,283	2,169	2,145	2,180	2,168	2,146	2,196
Services	18,025	17,047	18,050	18,684	18,729	19,583	20,305
Durable Manufacturing	18,366	17,264	16,400	16,217	16,399	16,601	16,566
Nondurable Manufacturing	7,871	7,088	6,917	7,032	6,907	6,906	6,727

Industry	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
Mining	778	747	682	684	724	684
Construction	1,936	1,982	2,062	2,155	2,141	2,086
Trans. & Utilities	9,393	9,373	9,773	10,053	10,044	9,694
Wholesale Trade	5,099	5,107	5,161	5,220	5,038	4,945
Retail Trade	13,700	13,750	14,093	14,299	14,515	14,700
FIRE	2,331	2,363	2,424	2,443	2,481	2,529
Services	21,516	21,898	22,897	24,612	24,190	24,241
Durable Manufacturing	17,179	17,224	16,994	17,066	16,198	15,338
Nondurable Manufacturing	6,780	6,639	6,505	6,442	6,118	6,056

Table 2.10: Industry Labor Input of Total Annual Hours for Females (in Millions)

Industry	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**
Mining	69	84	87	83	85	112	107
Construction	219	163	175	190	218	218	225
Trans. & Utilities	2,808	2,512	2,647	2,695	2,826	2,898	2,907
Wholesale Trade	5,510	4,822	5,207	5,093	5,389	5,376	5,442
Retail Trade	8,025	7,602	8,094	8,207	8,667	8,845	8,950
FIRE	2,207	2,142	2,252	2,275	2,317	2,266	2,257
Services	23,104	22,294	22,966	23,435	24,648	25,821	26,829
Durable Manufacturing	6,038	5,246	5,378	5,218	5,418	5,422	5,411
Nondurable Manufacturing	4,506	4,553	4,401	4,263	4,269	4,100	3,933

Industry	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
Mining	104	100	94	100	97	96
Construction	248	257	282	303	303	296
Trans. & Utilities	3,121	3,117	3,263	3,403	3,376	3,118
Wholesale Trade	5,766	5,776	5,801	5,916	5,605	5,410
Retail Trade	9,550	9,747	9,969	10,160	10,189	10,176
FIRE	2,457	2,525	2,563	2,578	2,614	2,609
Services	28,974	29,939	31,010	32,845	32,971	32,915
Durable Manufacturing	5,623	5,603	5,581	5,646	5,273	4,736
Nondurable Manufacturing	3,953	3,852	3,753	3,671	3,456	3,279

an increase in the number of hours at work of 7.08% on average. The greatest percentage reduction for each gender are as follows: a 70.53% reduction in hours of males in the Mining industry and a 37.42% decrease in hours of females within Nondurable Manufacturing. The largest observed increase is within Services, with close to a 30% increase in hours between the two years.

The index of labor quality ($\triangle \ln LC$) for males and females utilizing each technique is summarized in Tables 11-14. As is the case with the price index, quality is also normalized to one in 2000. This index captures the changing composition of the labor force, defined as the ratio of the volume of the labor input to the sum of all hours worked within each sector.

In reviewing the price index of labor for males in Tables 2.1 and 2.3, it is apparent that the Jorgensonian and Beckerian derivation of the price of labor results in indices with disparate interpretations. The BLS method has an index of the price of labor, normalized to one in 2000, that ranges between 0.98 and 1.01 in every year. It is the case that the Census-proposed alternative price takes on values that more greatly deviate over the years. In 1990, the index of the price of labor falls between 0.80 and 1.00. By 2002, this is compressed to the range covering 0.91 and 0.95. The increased sensitivity of the changing composition of the work force that is captured by the Beckerian method is apparent when examining these two tables in tangent.

Tables 2.2 and 2.4 similarly demonstrate that for employed women, the price index of labor exhibits more fluctuations in the Census-proposed alternative. The normalized price of labor using the BLS methodology ranges in 1990 from 1.00-1.03 and in 2002 from 0.98-1.00. However, the Census alternative price index of labor indicates a shifting from 0.90-1.37 in 1990 to 0.91-0.94 in 2002. The average

Table 2.11: Bureau of Labor Statistics' Index of Labor Quality for Males

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	1.0578	1.0697	1.0453	1.0400	1.0302	1.0319	1.0298
Construction	1.0323	1.0260	1.0190	1.0190	1.0161	1.0134	1.0108
Trans. & Utilities	1.0392	1.0339	1.0262	1.0277	1.0229	1.0197	1.0154
Wholesale Trade	1.0284	1.0304	1.0280	1.0286	1.0249	1.0209	1.0171
Retail Trade	1.0265	1.0298	1.0235	1.0244	1.0223	1.0197	1.0172
FIRE	1.0277	1.0218	1.0171	1.0198	1.0149	1.0083	1.0087
Services	1.0289	1.0255	1.0196	1.0193	1.0175	1.0144	1.0124
Durable Manufacturing	1.0370	1.0309	1.0220	1.0245	1.0224	1.0226	1.0181
Nondurable Manufacturing	1.0455	1.0350	1.0278	1.0303	1.0268	1.0254	1.0171

Industry	1997	1998	1999	2000	2001	2002
Mining	1.0243	1.0177	0.9993	1.0000	1.0032	0.9883
Construction	1.0055	1.0041	1.0026	1.0000	0.9971	0.9953
Trans. & Utilities	1.0098	1.0079	1.0028	1.0000	0.9962	0.9866
Wholesale Trade	1.0124	1.0105	1.0050	1.0000	0.9934	0.9868
Retail Trade	1.0118	1.0080	1.0041	1.0000	0.9970	0.9964
FIRE	1.0053	1.0070	1.0052	1.0000	0.9977	0.9951
Services	1.0078	1.0071	1.0048	1.0000	0.9970	0.9941
Durable Manufacturing	1.0131	1.0105	1.0046	1.0000	0.9918	0.9800
Nondurable Manufacturing	1.0119	1.0089	1.0043	1.0000	0.9928	0.9875

Table 2.12: Bureau of Labor Statistics' Index of Labor Quality for Females

Industry	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**
Mining	1.1284	1.1114	1.0989	1.0882	1.0786	1.0452	1.0380
Construction	1.1161	1.0537	1.0432	1.0363	1.0230	1.0218	1.0199
Trans. & Utilities	1.0572	1.0462	1.0382	1.0339	1.0264	1.0245	1.0203
Wholesale Trade	1.0527	1.0432	1.0377	1.0326	1.0264	1.0246	1.0198
Retail Trade	1.0378	1.0363	1.0303	1.0283	1.0233	1.0217	1.0192
FIRE	1.0617	1.0591	1.0511	1.0482	1.0395	1.0320	1.0281
Services	1.0468	1.0457	1.0364	1.0339	1.0281	1.0249	1.0219
Durable Manufacturing	1.0608	1.0489	1.0397	1.0339	1.0267	1.0265	1.0202
Nondurable Manufacturing	1.0494	1.0429	1.0315	1.0266	1.0223	1.0219	1.0152

Industry	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
Mining	1.0290	1.0224	1.0089	1.0000	0.9969	0.9873
Construction	1.0112	1.0083	1.0056	1.0000	0.9999	0.9944
Trans. & Utilities	1.0118	1.0083	1.0051	1.0000	0.9962	0.9797
Wholesale Trade	1.0118	1.0086	1.0056	1.0000	0.9940	0.9830
Retail Trade	1.0123	1.0083	1.0061	1.0000	0.9980	0.9952
FIRE	1.0176	1.0139	1.0101	1.0000	0.9954	0.9842
Services	1.0137	1.0097	1.0073	1.0000	0.9968	0.9895
Durable Manufacturing	1.0126	1.0092	1.0057	1.0000	0.9912	0.9701
Nondurable Manufacturing	1.0078	1.0065	1.0052	1.0000	0.9941	0.9855

Table 2.13: Census-Proposed Alternative Index of Labor Quality for Males

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	0.9164	0.9198	0.9397	0.9517	0.9637	0.9881	0.9882
Construction	0.9859	0.9829	0.9838	0.9822	0.9868	0.9919	0.9934
Trans. & Utilities	1.0466	1.0373	1.0107	1.0076	1.0035	1.0015	0.9997
Wholesale Trade	1.0591	1.0513	1.0127	1.0063	0.9997	0.9970	0.9974
Retail Trade	1.0653	1.0550	1.0121	1.0096	1.0056	1.0064	0.9978
FIRE	1.0198	1.0113	0.9944	1.0016	0.9957	0.9904	0.9897
Services	0.9768	0.9788	0.9955	0.9971	1.0002	0.9973	0.9952
Durable Manufacturing	1.0129	1.0038	0.9943	0.9954	0.9963	0.9977	0.9954
Nondurable Manufacturing	0.9869	0.9798	0.9870	0.9909	0.9925	0.9938	0.9926

Industry	1997	1998	1999	2000	2001	2002	ρ
Mining	0.9830	0.9877	0.9969	1.0000	0.9973	1.0059	-0.9177
Construction	0.9961	0.9975	1.0007	1.0000	0.9978	1.0048	-0.8992
Trans. & Utilities	1.0004	0.9979	0.9974	1.0000	0.9966	0.9979	0.7691
Wholesale Trade	0.9982	0.9986	1.0010	1.0000	0.9969	1.0033	0.4999
Retail Trade	0.9979	0.9858	0.9764	1.0000	0.9936	0.9870	0.7546
FIRE	0.9920	0.9970	0.9959	1.0000	0.9968	0.9990	0.6382
Services	1.0002	1.0017	1.0058	1.0000	1.0023	1.0005	-0.7719
Durable Manufacturing	0.9985	0.9977	0.9981	1.0000	0.9959	0.9939	0.5744
Nondurable Manufacturing	0.9953	0.9964	0.9993	1.0000	0.9980	0.9973	-0.8054

Table 2.14: Census-Proposed Alternative Index of Labor Quality for Females

Industry	1990	1991	1992	1993	1994	1995	1996
Mining	1.1115	1.0796	1.0413	1.0357	1.0328	0.9900	0.9979
Construction	1.1287	1.0608	1.0308	1.0225	1.0087	1.0116	1.0132
Trans. & Utilities	1.0505	1.0350	1.0133	1.0081	1.0025	1.0015	1.0010
Wholesale Trade	1.0201	1.0155	0.9912	0.9903	0.9870	0.9966	0.9967
Retail Trade	1.1448	1.1246	1.0552	1.0345	1.0234	1.0290	1.0185
FIRE	1.0973	1.0852	1.0385	1.0264	1.0155	1.0117	1.0104
Services	1.0466	1.0374	1.0358	1.0299	1.0222	1.0149	1.0133
Durable Manufacturing	0.9867	0.9747	0.9833	0.9876	0.9901	0.9916	0.9934
Nondurable Manufacturing	0.9598	0.9495	0.9796	0.9917	0.9952	0.9912	0.9926

Industry	1997	1998	1999	2000	2001	2002	ρ
Mining	1.0011	1.0055	1.0040	1.0000	1.0060	1.0067	0.8441
Construction	1.0119	1.0041	1.0030	1.0000	0.9986	0.9992	0.9762
Trans. & Utilities	1.0011	0.9998	1.0010	1.0000	0.9991	0.9941	0.8249
Wholesale Trade	0.9956	0.9949	1.0013	1.0000	1.0041	1.0056	0.1781
Retail Trade	1.0150	1.0002	0.9971	1.0000	0.9909	0.9821	0.8706
FIRE	1.0086	1.0027	1.0043	1.0000	0.9976	0.9933	0.8281
Services	1.0125	1.0046	1.0058	1.0000	0.9949	0.9905	0.9800
Durable Manufacturing	0.9964	0.9977	0.9982	1.0000	0.9974	0.9949	-0.7456
Nondurable Manufacturing	1.0022	1.0011	1.0016	1.0000	0.9951	0.9996	-0.8228

decrease in the Census-proposed index across all industries from 1990 to 2002 is 0.10, while for the BLS the average decrease in the index over that time period is 0.02.

Observed shifts in the index of labor quality, the key focus of this analysis, can be attributed two main sources: changes in total hours and in the education, experience, and gender composition of the work force over time. Table 2.11 illustrates that using the BLS method, males in 1990 in every industry have an index of quality that ranges between 1.03 and 1.06. By 2002, this has fallen to between 0.98 and 1.00. The Census-proposed alternative measure in Table 2.13 shows the range tightening from 0.91-1.07 to 0.99-1.01. On average, labor quality fell by 0.05 between 1990 and 2002 according to BLS techniques and by 0.01 using the alternative method.

Likewise, for women the quality index in Table 2.12 is between 1.04 and 1.13 in 1990 and between 0.97 and 1.00 in 2002 using the BLS definitions. The Census-proposed alternative, presented in Table 2.14, indicates these ranges are 0.96-1.14 and 0.98-1.01 in 1990 and 2002, respectively. Average labor quality across all industries fell by 0.08 over the years in the study when employing BLS techniques and by 0.06 when using the alternative method.

Deceptively, these findings would seem to imply that the two methods may be similar. However, a closer inspection reveals that the industries that underlie these ranges differ. Within industry correlation of the quality index (excluding the year 2000) reveals that the likeness is not as apparent at a detailed level of examination. In fact, values of the index for men in Mining, Construction, Services, and Nondurable Manufacturing are highly negatively correlated. Women in Durable and Nondurable Manufacturing have quality indices that are negatively correlated across the methods, but all industries other than the aforementioned and Wholesale Trade are have highly positively correlated indices.

While aggregate hours are a function of labor composition, the total hours output by workers in the economy remain constant in each year. This sum is identically input into the BLS and Census-proposed alternative formulae. Thus, the dissimilarities observed across comparable tables are mainly the result of the price of labor. This value is used in weighting the index of the labor inputs, which is incorporated into the definition of the index of quality.

2.6 Conclusion

Additional research is required to fully understand the depth of the impact that the inclusion of Beckerian prices instead of Jorgensonian prices has upon the index of the quality of labor. The models used to derive the prices of labor capture distinctly unique aspects of the changing composition of the labor force. While the Jorgensonian (BLS) price indicator reflects returns to various characteristics, the Beckerian (Census-proposed alternative) price captures the effect of industry of human capital for each demographic group. This latter definition allows for more variability in the indices examined.

Chapter 3

Creating a Human Capital Dataset to Explore Productivity in the U. S. Economy

The LEHD infrastructure files utilized in generating results for 2 require much preparation in advance of estimating a fixed effects wage model from which the human capital measures are derived. This chapter outlines the data sources and steps taken to clean these files, correct topcoded earnings, impute missing jobs, impute the corresponding missing wage and salary income, generate a measure of work experience, derive annual hours for each job, account for selection into and out of the sample, and create national weights.

3.1 Input File Data Preparation

The Longitudinal Employer-Household Dynamics (LEHD) Program at the U. S. Bureau of the Census currently has data through Memorandums of Understanding with a number of partner states that include the states of Alabama, Arkansas, California, Colorado, Delaware, Florida, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Maryland, Maine, Minnesota, Missouri, Montana, North Carolina, North Dakota, New Jersey, New Mexico, Oklahoma, Oregon, Pennsylvania, South Carolina, Texas, Virginia, Vermont, Washington, Wisconsin, and West Virginia for varying years of coverage. These data include state Unemployment Insurance (UI) wage records and the Quarterly Census of Employment and Wages (QCEW), formally the ES-202 files. The quarters of entry for these two data types are illustrated by Tables 3.1 and 3.2.[1]

The UI wage records contain information about the quarterly wages of each covered individual employed by a firm located in that state. These are year-quarter-person files with a State Employer Identification Number (SEIN) associated with each job held. Since these records are collected for UI tax purposes, a small fraction of establishments are not covered. In particular, wages of those who are either self-employed, Federal workers, employed by small agricultural entities, or work for philanthropic or religious organizations are not included. Despite this, these files provide employment and earnings information from virtually all establishments in each state and for every worker associated with these places of business. When converted into a year format from a year-quarter format, the UI wage record files becomes the Employment History File (EHF) for each state.

The ES-202 files contain employer information. They include the physical location, total quarterly wages, detailed industry code, business ownership type, and total employment in each month of every year for each firm. The start date of each SEIN is also contained in this file, as are predecessor SEINs for each firm. These enable mergers and outbreaks of businesses to be observed. Unfortunately, the SEINs are state-specific identifiers that do not translate across state boundaries. As a result, employees of national companies cannot be collectively grouped. These

[1]The earliest coverage date used in this study is 1990. The states of Colorado, Idaho, Illinois, Indiana, Kansas, Maryland, Missouri, Washington, and Wisconsin all have data in this period. The other states enter the data as follows: California, North Carolina, Oregon, and Pennsylvania in 1991; Florida in 1992; Montana in 1993; Minnesota in 1994; New Mexico and Texas in 1995; Kentucky, Maine, and New Jersey in 1996; West Virginia in 1997; Delaware, Iowa, North Dakota, South Carolina, and Virginia in 1998; Oklahoma and Vermont in 2000; Alaska in 2001; Alabama in 2002. All data span until 2003, with the series for the states of all but California and North Carolina continuing into 2004.

Table 3.1: Entry of Quarterly Unemployment Insurance Wage Records into LEHD Snapshot

	1990				1991				1992				1993				1994				1995				1996				1997			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
AL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
DE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FL	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ID	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
MD	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ME	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
MN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MT	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NC	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
NM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
OK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OR	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PA	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TX	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
VA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
WV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
qtotal	9	9	9	9	12	12	13	13	13	13	13	14	15	15	15	15	15	15	16	16	17	17	18	18	20	20	20	21	22	22	22	22

Table 3.1 (Continued)

	1998				1999				2000				2001				2002				2003				2004		
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**
AL	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0
CA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
CO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
DE	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
FL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
IA	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
ID	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
IN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
KS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
KY	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
MD	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
ME	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
MN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
MT	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
NC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
ND	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
NJ	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
NM	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
OK	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
OR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
PA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
SC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
TX	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
VA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
VT	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
WA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
WV	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
qtotal	25	25	26	27	27	27	27	27	29	29	29	29	30	30	30	30	30	30	31	31	31	31	31	31	29	5	2

Table 3.2: Entry of Quarterly ES-202 Records into LEHD Snapshot

	1990				1991				1992				1993				1994				1995				1996				1997			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
AL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CA	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
DE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
FL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ID	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MD	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ME	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
MN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MT	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NC	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
NM	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PA	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TX	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
VA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
VT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
WV	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
qtotal	13	13	13	13	17	17	17	17	17	17	17	17	18	18	18	18	18	18	19	19	20	20	21	21	22	22	22	22	23	23	23	23

Table 3.2 (Continued)

	1998				**1999**				**2000**				**2001**				**2002**				**2003**				**2004**		
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**
AL	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0
CA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
CO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
DE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
FL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
IA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
ID	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
IN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
KS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
KY	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
MD	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
ME	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
MN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
MT	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
NC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
ND	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
NJ	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
NM	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
OK	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
OR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
PA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
SC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
TX	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
VA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
VT	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
WA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
WV	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
qtotal	26	26	26	26	27	27	27	27	28	28	28	28	30	30	30	30	30	30	31	31	31	31	31	31	29	5	2

year-quarter-establishment files are grouped to form the Employer Characteristics File (ECF) for each state.

These infrastructure files require data preparation in advance of estimating a model to derive measures of human capital. Table 3.3 outlines the final year ranges and summarizes some of the data work performed on the base input files.[2] This table is based on the metadata for the 2004 snapshot. Although thirty-one states are available, Arkansas has only one complete year and is dropped from the sample. Kansas has a large amount of missing data in the first quarter of 1990, while Colorado has a large amount of missing data in the fourth quarter of 1990. Start date for those states have been pushed back one year. ECF data is not available for some years for ID, IN, and KY. The human capital estimation does not require ECF variables, so all available EHF years are used. The unaltered Employment History Files for eleven states contain topcoded values, while those of five states are affected by incomplete data quarters and require jobs and earnings to be imputed.[3] Additionally, an hours imputation is necessary so that a measure of annual hours of work can be incorporated into our model. A Heckit selection model corrects for movements into and out of LEHD-covered states. And, finally, a series of national weights are generated to adjust the productivity results from our sample of states to be representative of the entire U. S. population. The human

[2]This table was created based on the metadata for the 2004 snapshot. Although 31 states are available, Arkansas has only 1 complete year and is dropped from the sample. Kansas has a large amount of missing data in 1990:1, while Colorado has a large amount of missing data in 1990:4. Start date for those states has been pushed back one year. ECF data is not available for some years for ID, IN, and KY. The HC estimation does not require ECF vars and all available EHF years will be used.

[3]Those states with topcoded earnings are California, Colorado, Florida, Idaho, Maryland, Maine, North Carolina, New Jersey, Oregon, Pennsylvania, and Virginia. Incomplete data quarters are as follows: Colorado, 1993q1; Illinois, 1992q1 and 1993q1; Kansas, 1992q4; Missouri, 1994q4; and Pennsylvania, 1996q4.

capital model itself is estimated using the set of full-year state Unemployment Insurance wage records outlined by Table 3.4. However, the coverage restrictions of the ES-202 described by Table 3.5 cause the ultimate covered set of states and years that can be weighted up to national totals for the productivity analysis to be those in Table 3.6.[4]

3.1.1 Correcting Topcoded Values

Many quarters of earnings data on the Employer History File (EHF) are censored, thus compressing the distribution by eliminating a large portion of the right tail. In order to recover this part of the distribution, we have implemented an earnings imputation procedure. The key insight required to understand our methodology is that the earnings percentiles for the topcoded (or censored) data that lie at least partially below the topcode value are sufficient statistics for the complete data equivalent. In the LEHD earnings data, the number of topcoded values is relatively small, implying that we could accurately estimate very small percentiles, but in practice deciles are sufficient. Using this information, we iteratively fit the two parameters (mean and standard deviation, with starting values from the censored data) that specify a lognormal distribution by minimizing the difference between the target and actual earnings deciles. The result is an estimate of the mean and standard deviation of the uncensored distribution. This is done for every year and quarter in Table 3.7 that we identify that earnings are affected by

[4] Due to insufficient sample size in 1990, the states of Colorado and Kansas have start dates in 1991. Three years of data are required for the Human Capital estimation model, and as a result the state of Arkansas has been dropped from the analysis.

Table 3.3: Year Ranges for Human Capital Estimation Sample by State

State	Year Begin	Year End	Years Use	Adjusted	In Sample	Adjusted Start Year	Notes
AL	2001	2003	3	No	1		
AR	2003	2003	1	No	0		One quarter less than EHF, but both run beyond 2003:4 (ECF 2004:1 and EHF 2004:2) Only one year of data; sample too small for estimation.
CA	1992	2003	12	No	1		Topcode correction.
CO	1990	2003	13	Yes	1	1991	EHF 1990:4 is missing a large number of records. Possible identifier problem. However, B looks fine in 1991:1. EHF impute done for 1993:1. Topcode correction.
DE	1999	2003	5	No	1		
FL	1993	2003	11	No	1		Topcode correction
IA	1999	2003	5	No	1		
ID	1990	2003	14	No	1		ECF starts in 1991:1, other data available from 1990:1. Topcode correction.
IL	1990	2003	14	No	1		EHF Impute done in 1992:1 and 1993:1
IN	1990	2003	14	No	1		ECF starts in 1998:1, other data available from 1990:1
KS	1990	2003	13	Yes	1	1991	1990:1 EHF data is not complete. EHF impute done for 1992:4
KY	1997	2003	7	No	1		ECF starts in 2001:1, other data available from 1997:1
MD	1990	2003	14	No	1		Topcode correction.
ME	1996	2003	8	No	1		Topcode correction.
MN	1995	2003	9	No	1		
MO	1990	2003	14	No	1		EHF Impute done for 1994:4
MT	1993	2003	11	No	1		
NC	1991	2003	13	No	1		Topcode correction.
ND	1998	2003	6	No	1		
NJ	1996	2003	8	No	1		Topcode correction.
NM	1996	2003	8	No	1		
OK	2000	2003	4	No	1		
OR	1991	2003	13	No	1		Topcode correction.
PA	1991	2003	13	No	1		EHF impute done for 1996:4. Topcode correction.
SC	1998	2003	6	No	1		
TX	1995	2003	9	No	1		
VA	1998	2003	6	No	1		Topcode correction.
VT	2000	2003	4	No	1		
WA	1990	2003	14	No	1		
WI	1990	2003	14	No	1		
WV	1997	2003	7	No	1		
Total					30		

Table 3.4: Full Year Presence of UI State Data in Human Capital Estimation Sample

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
AL	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CA	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0
CO	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
DE	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
FL	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0
IA	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
ID	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
IN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
KS	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
KY	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
MD	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
ME	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
MN	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
MO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
MT	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0
NC	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
ND	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
NJ	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
NM	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
OK	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0
OR	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
PA	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SC	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
TX	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
VA	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
VT	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0
WA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
WV	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
Total	7	12	13	15	15	17	20	22	25	27	29	30	30	30	0

Table 3.5: Full Year Presence of ES-202 State Data in Human Capital Estimation Sample

	1990	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
AL	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
CA	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
CO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
DE	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
FL	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0
IA	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
ID	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
IN	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
KS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
KY	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
MD	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
ME	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
MN	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
MO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
MT	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0
NC	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
ND	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
NJ	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
NM	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
OK	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
OR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
PA	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SC	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
TX	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
VA	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
VT	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0
WA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
WV	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
Total	10	14	14	16	16	18	21	22	25	27	28	30	30	31	0

Table 3.6: Full Year Presence of UI and ES-202 State Data in Weighted Human Capital Estimation Sample

	1990	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
AL	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CA	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0
CO	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
DE	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
FL	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0
IA	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
ID	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
IN	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
KS	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
KY	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
MD	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
ME	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
MN	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
MO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
MT	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0
NC	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
ND	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
NJ	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
NM	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
OK	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0
OR	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
PA	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SC	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
TX	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
VA	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
VT	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0
WA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
WV	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
Total	5	11	12	14	14	16	19	20	24	26	28	30	30	30	0

topcoding.[5]

To impute earnings values, we use the estimated parameters to draw from a lognormal over the portion of the distribution that lies above the censored value. A random number from the uniform distribution is mapped to an earnings value using the inverse truncated normal CDF.

Methodology

We begin by assuming earnings, w, follow a lognormal distribution defined by

$$f(w; \mu, \sigma) = \frac{1}{x\sqrt{2\pi\sigma}} \exp\left[-\frac{1}{2\sigma^2}\left(\log w - \mu\right)^2\right].$$

This parametric approximation provides the necessary structure, thus reducing the number of parameters or dimensionality of the problem. This is a reasonable distribution to use for earnings data; the distribution is bounded by 0 and ∞, with most of its mass near the lower bound of 0. As you can see, the lognormal also implies that $z = \log(w)$ is normally distributed. We take advantage of this fact by always working with earnings in logs, exponentiating when necessary to transform the log values back into dollars.

The normal distribution is completely defined by two parameters; the mean, μ, and the standard deviation, σ. The problem thus requires estimating these two parameters using information from the observed (censored) earnings data. Given that the data are censored, we know if a worker has quarterly earnings above a certain amount, but we do not know the exact earnings value. The key insight is that we can calculate most percentiles of the uncensored distribution using only the censored data since we know over what region the actual earnings values lie

[5]The states of California, Colorado, Florida, Idaho, Maine, Maryland, North Carolina, New Jersey, Oregon, Pennsylvania, and Virginia are the only states affected by earnings censoring.

Table 3.7: States with Topcoded Values

State	**Year**	**Qtr**	**Observations**	**Obs at Max**	**% at Max**
CA	1995	3	14,902,874	6	0.00004
CA	1995	4	14,753,273	13	0.00009
CA	1997	1	14,923,350	11	0.00007
CO	1990	1	1,697,737	109	0.00642
CO	1990	2	1,697,648	28	0.00165
CO	1990	3	1,503,148	88	0.00585
CO	1990	4	1,732,591	349	0.02014
CO	1991	1	1,664,448	567	0.03407
CO	1991	2	1,753,955	703	0.04008
CO	1991	3	1,785,803	640	0.03584
CO	1991	4	1,601,246	1,592	0.09942
CO	1992	1	1,729,840	818	0.04729
CO	1992	2	1,839,364	730	0.03969
CO	1992	3	1,883,300	762	0.04046
CO	1992	4	1,852,452	2,556	0.13798
CO	1993	1	122,765	6	0.00489
CO	1993	2	1,946,200	776	0.03987
CO	1993	3	2,008,868	785	0.03908
CO	1993	4	1,929,364	2,736	0.14181
CO	1994	1	1,860,268	822	0.04419
CO	1994	2	1,973,115	800	0.04055
CO	1994	3	1,994,976	849	0.04256
CO	1994	4	1,961,804	2,289	0.11668
CO	1995	1	1,914,041	1,012	0.05287
CO	1995	2	2,022,625	893	0.04415
CO	1995	3	2,077,960	922	0.04437
CO	1995	4	2,038,503	2,429	0.11916
CO	1996	1	2,108,300	1,072	0.05085
CO	1996	2	2,243,518	1,008	0.04493
CO	1996	3	2,292,266	1,023	0.04463
CO	1996	4	2,232,101	2,632	0.11792
CO	1997	1	2,182,916	1,438	0.06588
CO	1997	2	2,283,105	1,194	0.05230
CO	1997	3	2,304,531	1,914	0.08305
CO	1997	4	2,170,188	3,108	0.14321
CO	1998	1	2,221,992	1,722	0.07750
CO	1998	2	2,344,978	1,283	0.05471
CO	1998	3	2,389,243	1,367	0.05721
CO	1998	4	2,281,911	3,582	0.15697
CO	1999	1	2,298,081	1,771	0.07706

Table 3.7 (Continued)

State	Year	Qtr	Observations	Obs at Max	% at Max
CO	1999	3	2,487,516	1,469	0.05905
CO	1999	4	2,434,380	3,753	0.15417
CO	2000	1	2,429,801	1,760	0.07243
CO	2000	2	2,567,912	1,442	0.05615
CO	2000	3	2,600,374	1,539	0.05918
CO	2000	4	2,457,220	3,343	0.13605
CO	2001	1	2,486,997	1,558	0.06265
CO	2001	2	2,601,993	1,404	0.05396
CO	2001	3	2,578,463	1,349	0.05232
CO	2001	4	2,400,287	3,038	0.12657
CO	2002	1	2,343,253	1,242	0.05300
CO	2002	2	2,417,552	1,176	0.04864
CO	2002	3	2,439,932	1,009	0.04135
CO	2002	4	2,355,963	2,565	0.10887
CO	2003	1	2,234,199	1,043	0.04668
CO	2003	2	2,317,698	945	0.04077
CO	2003	3	2,399,266	1,047	0.04364
CO	2003	4	2,354,733	2,370	0.10065
FL	1992	4	6,445,800	13,068	0.20274
FL	1993	1	6,455,516	3,602	0.05580
FL	1993	2	6,614,831	5,084	0.07686
FL	1993	3	6,608,275	4,935	0.07468
FL	1993	4	6,689,914	12,903	0.19287
FL	1994	1	6,761,016	4,497	0.06651
FL	1994	2	6,926,588	4,868	0.07028
FL	1994	3	6,870,112	5,191	0.07556
FL	1994	4	6,977,509	12,011	0.17214
FL	1995	1	6,957,884	5,645	0.08113
FL	1995	2	7,094,176	5,721	0.08064
FL	1995	3	6,933,243	5,832	0.08412
FL	1995	4	7,051,898	12,896	0.18287
FL	1996	1	7,054,409	6,634	0.09404
FL	1996	2	7,343,859	6,408	0.08726
FL	1996	3	7,243,696	6,426	0.08871
FL	1996	4	7,355,967	14,168	0.19261
FL	1997	1	7,185,339	7,555	0.10514
FL	1997	2	6,249,492	5,754	0.09207
FL	1997	3	7,055,511	28	0.00040
FL	1997	4	7,609,541	25	0.00033
FL	1998	1	7,473,461	26	0.00035
FL	1998	2	7,575,275	13	0.00017

Table 3.7 (Continued)

State	Year	Qtr	Observations	Obs at Max	% at Max
FL	1998	3	7,629,252	8	0.00010
FL	1998	4	7,750,292	15	0.00019
FL	1999	1	7,802,605	15	0.00019
FL	1999	2	7,882,227	9	0.00011
FL	1999	3	7,668,492	17	0.00022
FL	1999	4	7,910,495	12	0.00015
FL	2000	1	7,611,207	15	0.00020
FL	2000	2	7,488,100	22	0.00029
FL	2000	3	7,672,229	13	0.00017
FL	2000	4	8,093,165	16	0.00020
FL	2001	1	8,007,734	21	0.00026
FL	2001	2	8,113,807	21	0.00026
FL	2001	3	8,014,294	17	0.00021
FL	2001	4	7,928,372	17	0.00021
FL	2002	1	7,919,644	16	0.00020
FL	2002	2	7,724,490	23	0.00030
FL	2002	3	8,163,081	20	0.00025
FL	2002	4	8,207,121	18	0.00022
FL	2003	1	7,980,684	14	0.00018
FL	2003	2	7,890,302	19	0.00024
FL	2003	3	7,916,383	25	0.00032
FL	2003	4	7,948,654	17	0.00021
ID	1990	1	422,092	131	0.03104
ID	1990	2	474,230	136	0.02868
ID	1990	3	499,915	144	0.02880
ID	1990	4	467,799	441	0.09427
ID	1991	1	435,232	110	0.02527
ID	1991	2	484,692	161	0.03322
ID	1991	3	513,588	175	0.03407
ID	1991	4	482,069	418	0.08671
ID	1992	1	453,550	178	0.03925
ID	1992	2	515,986	186	0.03605
ID	1992	3	539,819	209	0.03872
ID	1992	4	505,574	553	0.10938
ID	1993	1	469,002	139	0.02964
ID	1993	2	535,127	203	0.03793
ID	1993	3	568,782	215	0.03780
ID	1993	4	540,114	572	0.10590
ID	1994	1	504,541	194	0.03845
ID	1994	2	570,318	259	0.04541
ID	1994	3	601,923	238	0.03954

Table 3.7 (Continued)

State	Year	Qtr	Observations	Obs at Max	% at Max
ID	1994	4	569,304	570	0.10012
ME	1998	4	663,667	2	0.00030
ME	1999	1	616,183	5	0.00081
ME	1999	2	684,806	9	0.00131
ME	1999	3	709,652	19	0.00268
ME	1999	4	683,237	7	0.00102
ME	2002	1	640,800	5	0.00078
ME	2002	3	717,702	5	0.00070
ME	2003	1	637,838	2	0.00031
ME	2003	2	693,564	6	0.00087
ME	2003	4	685,978	10	0.00146
MD	1985	2	2,029,675	52	0.00256
MD	1986	3	2,088,383	53	0.00254
MD	1986	4	2,081,431	6	0.00029
MD	1987	1	2,073,054	9	0.00043
MD	1987	2	2,190,971	4	0.00018
MD	1987	3	2,248,068	7	0.00031
MD	1987	4	2,186,220	12	0.00055
MD	1988	1	2,162,669	21	0.00097
MD	1988	2	2,269,048	29	0.00128
MD	1988	3	2,318,492	16	0.00069
MD	1988	4	2,239,553	18	0.00080
MD	1989	1	2,204,268	11	0.00050
MD	1989	2	2,326,443	8	0.00034
MD	1989	3	2,338,861	12	0.00051
MD	1989	4	2,279,650	43	0.00189
MD	1990	1	2,205,918	2	0.00009
MD	1990	2	2,311,521	15	0.00065
MD	1990	3	2,249,084	15	0.00067
MD	1990	4	2,212,895	69	0.00312
MD	1991	1	2,132,826	18	0.00084
MD	1991	2	2,214,753	11	0.00050
MD	1991	3	2,071,069	33	0.00159
MD	1991	4	2,022,731	25	0.00124
MD	1992	1	1,967,574	3	0.00015
MD	1992	2	2,035,540	29	0.00142
MD	1992	3	2,081,827	8	0.00038
MD	1992	4	1,979,059	6	0.00030
MD	1993	1	1,991,214	10	0.00050
MD	1993	2	2,109,027	7	0.00033
MD	1993	3	2,115,675	13	0.00061

Table 3.7 (Continued)

State	Year	Qtr	Observations	Obs at Max	% at Max
MD	1993	4	2,053,960	21	0.00102
MD	1994	1	2,023,526	6	0.00030
MD	1994	2	2,167,135	12	0.00055
MD	1994	3	2,192,939	22	0.00100
MD	1994	4	2,154,485	36	0.00167
MD	1995	1	2,150,044	46	0.00214
MD	1995	2	2,407,690	99	0.00411
MD	1995	3	2,401,372	39	0.00162
MD	1995	4	2,316,521	132	0.00570
MD	1996	1	2,288,810	53	0.00232
MD	1996	2	2,369,004	57	0.00241
MD	1996	3	2,405,932	58	0.00241
MD	1996	4	2,362,822	212	0.00897
MD	1997	1	2,242,758	365	0.01627
MD	1997	2	2,389,993	318	0.01331
MD	1997	3	2,438,340	292	0.01198
MD	1997	4	2,383,146	1,136	0.04767
MD	1998	1	2,282,330	4,851	0.21255
MD	1998	2	2,421,437	4,620	0.19080
MD	1998	3	2,374,003	4,612	0.19427
MD	1998	4	2,320,932	13,089	0.56395
MD	1999	1	2,325,360	7,843	0.33728
MD	1999	2	2,488,287	5,921	0.23795
MD	1999	3	2,535,928	4,812	0.18975
MD	1999	4	2,516,198	8,037	0.31941
MD	2000	1	2,438,060	5,353	0.21956
MD	2000	2	2,633,688	7,472	0.28371
MD	2000	3	2,653,094	5,864	0.22102
MD	2000	4	2,564,590	5,073	0.19781
MD	2001	1	2,531,321	657	0.02595
MD	2001	2	2,655,959	427	0.01608
MD	2001	3	2,689,539	422	0.01569
MD	2001	4	2,646,346	797	0.03012
MD	2002	1	2,545,726	291	0.01143
MD	2002	2	2,645,036	280	0.01059
MD	2002	3	2,666,259	161	0.00604
MD	2002	4	2,620,963	402	0.01534
MN	1998	4	2,905,130	2	0.00007
MN	1999	1	2,799,898	2	0.00007
NJ	1996	2	3,408,551	6	0.00018
NJ	1996	3	3,533,704	17	0.00048

Table 3.7 (Continued)

State	Year	Qtr	Observations	Obs at Max	% at Max
NJ	1996	4	3,485,088	40	0.00115
NJ	1997	2	3,676,737	8	0.00022
NJ	1997	3	3,813,508	13	0.00034
NJ	1997	4	3,770,354	18	0.00048
NJ	1998	1	3,725,179	19	0.00051
NJ	1998	2	3,924,851	3	0.00008
NJ	1998	3	3,895,927	15	0.00039
NJ	1998	4	3,939,352	19	0.00048
NJ	1999	1	3,817,393	24	0.00063
NJ	1999	2	4,126,251	38	0.00092
NJ	1999	3	4,258,023	50	0.00117
NJ	1999	4	4,279,123	32	0.00075
NJ	2000	1	4,215,038	59	0.00140
NJ	2000	2	4,350,474	42	0.00097
NJ	2000	3	4,571,503	23	0.00050
NJ	2000	4	4,414,847	37	0.00084
NJ	2001	1	4,350,784	77	0.00177
NJ	2001	2	4,496,840	37	0.00082
NJ	2001	3	4,587,512	25	0.00054
NJ	2001	4	4,452,433	16	0.00036
NJ	2002	1	4,302,218	25	0.00058
NJ	2002	2	4,408,494	29	0.00066
NJ	2002	3	4,482,630	4	0.00009
NJ	2002	4	4,335,786	10	0.00023
NJ	2003	1	4,099,189	5	0.00012
NJ	2003	2	4,276,168	16	0.00037
NJ	2003	3	4,340,601	14	0.00032
NJ	2003	4	4,235,165	7	0.00017
NC	1993	2	3,753,838	2	0.00005
NC	1993	3	3,861,357	2	0.00005
NC	1993	4	3,803,159	9	0.00024
NC	1994	1	3,719,746	10	0.00027
NC	1994	2	3,934,959	2	0.00005
NC	1994	4	3,931,309	3	0.00008
NC	1995	1	3,895,991	13	0.00033
NC	1995	4	4,092,612	3	0.00007
NC	1996	1	4,024,774	21	0.00052
NC	1996	2	4,244,277	2	0.00005
NC	1996	3	4,325,022	2	0.00005
NC	1996	4	4,210,213	5	0.00012
NC	1997	3	4,399,468	2	0.00005

Table 3.7 (Continued)

State	Year	Qtr	Observations	Obs at Max	% at Max
NC	1997	4	4,292,481	4	0.00009
NC	1998	2	4,456,221	5	0.00011
NC	1998	3	4,532,574	6	0.00013
NC	1998	4	4,422,544	6	0.00014
OR	1991	1	1,377,440	365	0.02650
OR	1991	3	1,525,970	391	0.02562
OR	1991	4	1,463,339	1,060	0.07244
OR	1992	1	1,382,933	520	0.03760
OR	1992	3	1,550,069	501	0.03232
OR	1993	1	1,417,711	397	0.02800
PA	1991	1	5,446,084	2,902	0.05329
PA	1991	2	5,619,095	3,030	0.05392
PA	1991	3	5,683,874	3,133	0.05512
PA	1991	4	5,559,918	7,949	0.14297
PA	1992	1	5,299,256	3,520	0.06642
PA	1992	2	5,589,013	3,524	0.06305
PA	1992	3	5,669,907	3,339	0.05889
PA	1992	4	5,585,882	10,112	0.18103
PA	1993	1	5,400,634	3,031	0.05612
PA	1993	2	5,675,938	3,462	0.06099
PA	1993	3	5,762,185	3,470	0.06022
PA	1993	4	5,706,876	9,859	0.17276
PA	1994	1	5,485,325	3,624	0.06607
PA	1994	2	5,805,650	3,534	0.06087
PA	1994	3	5,937,042	3,758	0.06330
PA	1994	4	5,848,279	9,519	0.16277
PA	1995	1	5,677,146	5,186	0.09135
PA	1995	2	5,897,346	4,425	0.07503
PA	1995	3	5,981,442	4,433	0.07411
PA	1995	4	5,878,869	10,513	0.17883
PA	1996	1	5,698,864	6,187	0.10857
PA	1996	2	5,980,121	4,960	0.08294
PA	1996	3	6,086,416	4,942	0.08120
PA	1996	4	59,763	112	0.18741
PA	1997	1	5,809,720	7,140	0.12290
PA	1997	2	6,071,395	5,486	0.09036
PA	1997	3	6,176,380	5,859	0.09486
PA	1997	4	6,103,568	13,535	0.22176
PA	1998	1	5,915,166	8,723	0.14747
PA	1998	2	6,203,775	6,858	0.11055
PA	1998	3	6,294,653	6,473	0.10283

Table 3.7 (Continued)

State	Year	Qtr	Observations	Obs at Max	% at Max
PA	1998	4	6,228,705	14,238	0.22859
PA	1999	1	5,996,041	9,693	0.16166
PA	1999	2	6,269,040	7,270	0.11597
PA	1999	3	6,350,377	7,355	0.11582
PA	1999	4	6,296,317	15,228	0.24186
PA	2000	1	6,125,450	11,334	0.18503
PA	2000	2	6,403,770	7,637	0.11926
PA	2000	3	6,473,644	7,890	0.12188
PA	2000	4	6,392,503	15,997	0.25025
PA	2001	1	6,125,999	12,746	0.20806
PA	2001	2	6,333,084	7,695	0.12150
PA	2001	3	6,313,914	7,648	0.12113
PA	2001	4	5,986,374	15,358	0.25655
PA	2002	1	6,034,055	12,282	0.20354
PA	2002	2	6,228,564	10,052	0.16139
PA	2002	3	6,349,458	7,455	0.11741
PA	2002	4	6,163,346	15,234	0.24717
PA	2003	1	5,812,014	12,672	0.21803
VA	1998	1	2,605,548	113	0.00434
VA	1998	2	3,055,041	101	0.00331
VA	1998	3	3,709,772	108	0.00291
VA	1998	4	3,646,341	239	0.00655
VA	1999	1	3,529,733	279	0.00790
VA	1999	2	3,733,353	338	0.00905
VA	2001	3	3,876,447	105	0.00271
VA	2001	4	3,733,773	229	0.00613
VA	2003	2	3,655,831	109	0.00298
VA	2003	4	3,642,362	195	0.00535

and if the bin is wide enough we can assign them to the correct percentile. Using these percentiles, the mean and standard deviation can then be estimated.

We use an iterative algorithm that minimizes the squared sum of the differences between the mass in the actual deciles (0.1) and the amount predicted for a given mean and standard deviation. Let $g(z; \mu, \sigma)$ represent the normal density approximation of the distribution of log earnings. Then the CDF can be represented as

$$G(x) = \int_0^x g(z)dz,$$

where x represents a value on the support of z. We then calculate the decile boundaries q_k^* using the censored data implicitly defined by

$$G(q_k^*) = \int_0^{q_k^*} g(z)dz = k \cdot 0.1$$

for $k = 0, 1, .., 10$. For $k = 1, 2, .., 10$ the estimated mass in each decile for a given μ and σ is

$$\Gamma(k; \mu, \sigma) = G(q_k^*; \mu, \sigma) - G(q_{k-1}^*; \mu, \sigma)$$

Holding the q_k^* constant, we search for the mean and standard deviation such that each $\Gamma(k; \mu, \sigma)$ is as close as possible to 0.1.

The resulting mean $\widehat{\mu}$ and standard deviation $\widehat{\sigma}$ are used in the final stage to impute an earnings value, $\widehat{z}$, which is our ultimate goal. The truncated density function $t(z)$ for the normal distribution is (with z_c equal to the censored earnings value):

$$t(z) = \frac{g(z|z > z_c)}{1 - G(z_c)},$$

which can be used to calculate the CDF as well

$$T(z) = \frac{G(z) - G(z_c)}{1 - G(z_c)}. \tag{3.1}$$

Equation (3.1) provides the crucial link between the truncated CDF and the CDF for the complete earnings distribution. To get an imputed earnings value, we draw a number between 0 and 1 using the uniform distribution. Conceptually, this number represents a value of $T(z)$, but we really need a value for $G(z)$. Using some simple algebra, we get equation (3.2), that maps the $T(\widehat{z})$ draw into the appropriate region of $G(z)$, the uncensored earnings distribution given by

$$G(\widehat{z}) = G(z_c) + (1 - G(z_c))T(\widehat{z}). \tag{3.2}$$

The final step is to use the inverse CDF for the normal distribution to translate the $G(\widehat{z})$ value into an earnings value. Since this process is performed in logs, the imputed earnings value is:

$$earn = \exp(G^{-1}(G(\widehat{z})).$$

In practice, only the standard normal inverse CDF is available in SAS. The following equation is used to transform the standard normal values returned by the *probit* function into the appropriate values for the mean $\widehat{\mu}$ and standard deviation $\widehat{\sigma}$ of $G(z)$ using

$$G^{-1} = \widehat{\mu} + probit(G(z))\sigma.$$

It is possible as well to get a few unreasonably large draws, so we impose a new topcode value. Thus, what we actually do is create a uniform topcode for all of the censored data.

One characteristic of the complete data is the very strong persistence in earnings for a given worker, thus it is not reasonable to assume all draws are independent. In an attempt to replicate this characteristic, we take a relatively conservative approach of assuming earnings are correlated over time for a person working at the same firm. For these records the draw is kept the same, but the estimated mean and standard deviation of earnings varies over time, thus placing them in the same relative point on the distribution each period.

3.1.2 Imputing Missing Jobs

By examining Quality Assurance records of the Quarterly Workforce Indicators produced by the Longitudinal Employer-Household Dynamics Program at the U.S. Census Bureau, it is straightforward to determine which states have holes in their Unemployment Insurance wage records. When more than 10% of the firms in a quarter are deemed to either have been born or have died, a hole is apparent in the data. Table 3.8 shows these rates for the states with incomplete data quarters.[6] Figure 3.1.2 illuminates the missing data problem by conditioning on same-SEIN employment in bordering quarters, while Table 3.9 breaks down the frequency of 3-quarter work patterns in the missing data quarter and two comparable complete quarters for each targeted state. States with incomplete data quarters require that we impute jobs and also the corresponding value of earnings in these missing data quarters. Jobs are imputed based on 3-quarter work patterns, a model which is defined below.

Basic Model

Basic probabilities are given by

$$\pi(e_{t-1}, e_t, e_{t+1}, m_t) = \Pr\left[\left(e_{t-1}, e_t, e_{t+1}\right), m_t\right]$$

[6] Colorado, 1993q1; Illinois, 1992q1 and 1993q1; Kansas, 1992q4; Missouri, 1994q4; and Pennsylvania, 1996q4. Note that in the table, % Deaths (t-1) is the percent of firm deaths in previous quarter; % Births (t+1) is the percent of firm births in following quarter.

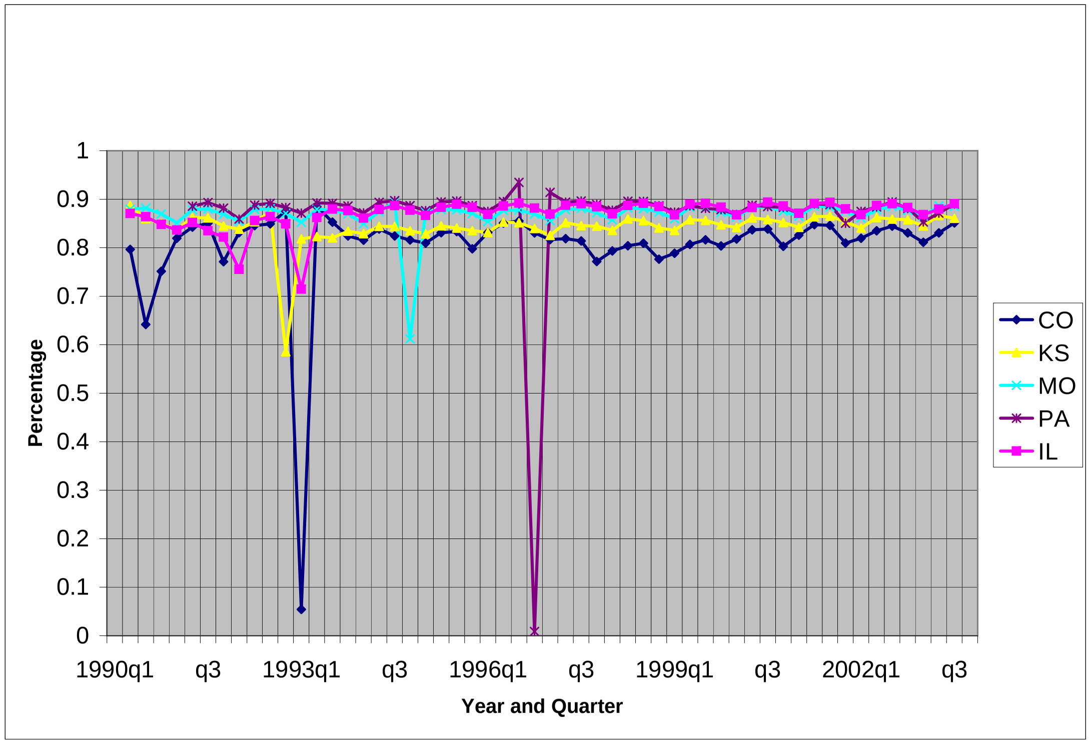

Figure 3.1: Employment Percentages Conditional on Employment at Any Job in Bordering Quarters

Table 3.8: States with Quarters of Missing Data

State	**Year**	**Qtr**	**% Deaths (t-1)**	**% Births (t+1)**
CO	1993	1	66	67
IL	1992	1	10	13
IL	1993	1	13	10
KS	1992	4	25	29
MO	1994	4	54	55
PA	1996	4	85	86

where (e_{t-1}, e_t, e_{t+1}) is the temporally-ordered sequence of employment status for periods $t-1$, t, and $t+1$ with

$$(e_{t-1}, e_t, e_{t+1}) \in \{(0,0,0), \ldots, (1,1,1))\}$$

and $m_t = 1$ indicates missing status for e_t (period t). Missing at random (Rubin 1987) assuming e_{t-1}, e_{t+1} never missing gives:

$$\begin{aligned}
\pi\left(e_t, m_t = 1 | e_{t-1}, e_{t+1}\right) &= \pi(e_t | e_{t-1}, e_{t+1}, m_t = 1)\pi(m_t = 1 | e_{t-1}, e_{t+1}) \\
&= \pi(m_t = 1 | e_{t-1}, e_t, e_{t+1})\pi(e_t | e_{t-1}, e_{t+1}) \\
&= \pi(m_t = 1 | e_{t-1}, e_{t+1})\pi(e_t | e_{t-1}, e_{t+1})
\end{aligned}$$

where the third line imposes MAR. Hence,

$$\begin{aligned}
\pi\left(e_t | e_{t-1}, e_{t+1}, m_t = 1\right) &= \frac{\pi(m_t = 1 | e_{t-1}, e_{t+1})\pi(e_t | e_{t-1}, e_{t+1})}{\pi(m_t = 1 | e_{t-1}, e_{t+1})} \\
&= \pi(e_t | e_{t-1}, e_{t+1})
\end{aligned}$$

which is correctly estimated by the conditional probability in the complete-data sample assuming that the complete-data sample is drawn from the same population as the missing-data sample. Data not missing at random implies

$$\pi\left(e_t, m_t = 1 | e_{t-1}, e_{t+1}\right) = \pi(m_t = 1 | e_{t-1}, e_t, e_{t+1})\pi(e_t | e_{t-1}, e_{t+1})$$

Table 3.9: Percentages of 3-quarter Work Patterns

Colorado: Missing Data in 1993q1

3-Quarter Work Pattern	**1993q1**	**1992q1**	**1994q1**
000	89.9206	88.6731	87.6826
001	2.6208	1.8375	2.0503
010	0.0453	0.6562	0.7301
011	0.1042	1.0903	1.4912
100	2.2928	1.7740	1.7671
101	4.6813	0.1602	0.1769
110	0.0597	0.9136	0.9633
111	0.2754	4.8952	5.1384

Illinois: Missing Data in 1992q1

3-Quarter Work Pattern	**1992q1**	**1991q1**	**1994q1**
000	86.7078	84.7153	84.5782
001	1.7486	1.9595	1.9742
010	0.5087	0.6091	0.5722
011	1.2503	1.2579	1.2410
100	1.6967	1.9863	1.9900
101	1.0608	0.2117	0.2157
110	0.9342	1.0824	1.0931
111	6.0929	8.1778	8.3357

Illinois: Missing Data in 1993q1

3-Quarter Work Pattern	**1993q1**	**1994q1**	**1995q1**
000	86.3884	84.5782	84.2568
001	1.9650	1.9742	2.0257
010	0.4683	0.5722	0.5796
011	1.0217	1.2410	1.3196
100	1.7887	1.9900	2.0674
101	1.4388	0.2157	0.2214
110	0.8305	1.0931	1.0799
111	6.0984	8.3357	8.4496

Table 3.9 (Continued)

Kansas: Missing Data in 1992q4

3-Quarter Work Pattern	1992q4	1991q4	1993q4
000	87.7159	86.2121	85.7310
001	1.8077	1.7040	1.8088
010	0.4624	0.8745	0.9364
011	0.6000	1.1965	1.2208
100	2.1926	2.0834	2.1972
101	2.1435	0.1898	0.2022
110	0.7197	1.1729	1.2314
111	4.3583	6.5667	6.6722

Missouri: Missing Data in 1994q4

3-Quarter Work Pattern	1994q4	1993q4	1994q4
000	86.1844	85.1864	87.4439
001	2.1776	1.7814	1.3220
010	0.4486	0.8876	0.6630
011	0.6547	1.1802	0.9142
100	2.6216	2.1258	1.6898
101	2.2406	0.1388	0.1042
110	0.6778	1.3323	1.0678
111	4.9948	7.3675	6.7951

Pennsylvania: Missing Data in 1996q4

3-Quarter Work Pattern	1996q4	1995q4	1997q4
000	83.7589	82.2231	83.5052
001	3.0910	1.8645	1.6650
010	0.0085	0.9210	0.7859
011	0.0130	1.4144	1.2460
100	3.6562	2.2592	2.0590
101	9.3651	0.2293	0.1781
110	0.0146	1.6345	1.3714
111	0.0928	9.4540	9.1895

and

$$\begin{aligned}\pi\left(e_t|e_{t-1},e_{t+1},m_t\right) &= \frac{\pi\left(e_{t-1},e_t,e_{t+1},m_t\right)}{\pi\left(e_{t-1},e_{t+1},m_t\right)} \\ &= \frac{\pi(m_t|e_{t-1},e_t,e_{t+1})\pi(e_{t-1},e_t,e_{t+1})}{\pi\left(e_{t-1},e_{t+1},m_t\right)} \\ &= \frac{\pi(m_t|e_{t-1},e_t,e_{t+1})}{\pi\left(m_t|e_{t-1},e_{t+1}\right)}\frac{\pi\left(e_{t-1},e_t,e_{t+1}\right)}{\pi\left(e_{t-1},e_{t+1}\right)}\end{aligned}$$

If (e_{t-1}, e_t, e_{t+1}) are observed for all cases in $\{(0,0,0),\ldots,(1,1,1)\}$ in the complete-data sample, then we can estimate $\pi\left(e_{t-1}, e_t, e_{t+1}\right)$ from that sample. The issue is how to estimate the ratio

$$\delta\left(m_t|e_{t-1},e_t,e_{t+1}\right) = \frac{\pi(m_t|e_{t-1},e_t,e_{t+1})}{\pi\left(m_t|e_{t-1},e_{t+1}\right)},$$

which measures the deviation of the missing-data sample from missing at random. If all $\delta\left(m_t|e_{t-1},e_t,e_{t+1}\right) = 1$, then missing at random holds for all cells of the missing-data sample. Otherwise, by combining the complete-data and missing-data samples, we can estimate some of the $\delta\left(m_t|e_{t-1},e_t,e_{t+1}\right)$.

Likelihood Function

For the complete-data sample

$$\pounds \propto \prod_{e_{t-1}}\prod_{e_t}\prod_{e_{t+1}}\pi(e_{t-1},e_t,e_{t+1})^{n(e_{t-1},e_t,e_{t+1})},$$

where $n\left(e_{t-1}, e_t, e_{t+1}\right)$ are the cell counts in the complete data. For the missing-data sample the conditional likelihood for the pair $\left(e_t, m_t\right)$ is

$$
\begin{aligned}
\pounds \propto & \prod_{e_{t-1}} \prod_{e_{t+1}} \left[\pi\left(e_t=1 | e_{t-1}, e_{t+1}, m_t=0\right) \pi\left(m_t=0 | e_{t-1}, e_{t+1}\right)\right]^{c\left(e_{t-1}, 1, e_{t+1}, 0\right)} \\
& \left[\pi\left(e_t=0 | e_{t-1}, e_{t+1}, m_t=0\right) \pi\left(m_t=0 | e_{t-1}, e_{t+1}\right)\right]^{c\left(e_{t-1}, 0, e_{t+1}, 0\right)} \\
& \left[\left(\pi\left(e_t=0 | e_{t-1}, e_{t+1}, m_t=1\right)+\pi\left(e_t=1 | e_{t-1}, e_{t+1}, m_t=1\right)\right) \times\right. \\
& \left.\pi\left(m_t=1 | e_{t-1}, e_{t+1}\right)\right]^{c\left(e_{t-1}, 0, e_{t+1}, 1\right)} \\
\propto & \prod_{e_{t-1}} \prod_{e_{t+1}} \left[\begin{array}{c} \frac{\pi(m_t=0|e_{t-1},e_t=1,e_{t+1})}{\pi(m_t=0|e_{t-1},e_{t+1})} \frac{\pi(e_{t-1},e_t=1,e_{t+1})}{\pi(e_{t-1},e_{t+1})} \times \\ \pi\left(m_t=0 | e_{t-1}, e_{t+1}\right) \end{array}\right]^{c\left(e_{t-1}, 1, e_{t+1}, 0\right)} \\
& \left[\begin{array}{c} \frac{\pi(m_t=0|e_{t-1},e_t=0,e_{t+1})}{\pi(m_t=0|e_{t-1},e_{t+1})} \frac{\pi(e_{t-1},e_t=0,e_{t+1})}{\pi(e_{t-1},e_{t+1})} \times \\ \pi\left(m_t=0 | e_{t-1}, e_{t+1}\right) \end{array}\right]^{c\left(e_{t-1}, 0, e_{t+1}, 0\right)} \\
& \left\{\begin{array}{c} \left[\frac{\pi(m_t=1|e_{t-1},e_t=0,e_{t+1})}{\pi(m_t=1|e_{t-1},e_{t+1})} \frac{\pi(e_{t-1},e_t=0,e_{t+1})}{\pi(e_{t-1},e_{t+1})}+\right. \\ \left.\frac{\pi(m_t=1|e_{t-1},e_t=1,e_{t+1})}{\pi(m_t=1|e_{t-1},e_{t+1})} \frac{\pi(e_{t-1},e_t=1,e_{t+1})}{\pi(e_{t-1},e_{t+1})}\right] \times \pi\left(m_t=1 | e_{t-1}, e_{t+1}\right) \end{array}\right\}^{c\left(e_{t-1}, 0, e_{t+1}, 1\right)} \\
\propto & \prod_{e_{t-1}} \prod_{e_{t+1}} \left[\begin{array}{c} \delta(m_t=0|e_{t-1},e_t=1,e_{t+1}) \frac{\pi(e_{t-1},e_t=1,e_{t+1})}{\pi(e_{t-1},e_{t+1})} \times \\ \pi\left(m_t=0 | e_{t-1}, e_{t+1}\right) \end{array}\right]^{c\left(e_{t-1}, 1, e_{t+1}, 0\right)} \\
& \left[\begin{array}{c} \delta(m_t=0|e_{t-1},e_t=0,e_{t+1}) \frac{\pi(e_{t-1},e_t=0,e_{t+1})}{\pi(e_{t-1},e_{t+1})} \times \\ \pi\left(m_t=0 | e_{t-1}, e_{t+1}\right) \end{array}\right]^{c\left(e_{t-1}, 0, e_{t+1}, 0\right)} \\
& \left\{\begin{array}{c} \left[\delta(m_t=1|e_{t-1},e_t=0,e_{t+1}) \frac{\pi(e_{t-1},e_t=0,e_{t+1})}{\pi(e_{t-1},e_{t+1})}+\right. \\ \left.\delta(m_t=1|e_{t-1},e_t=1,e_{t+1}) \frac{\pi(e_{t-1},e_t=1,e_{t+1})}{\pi(e_{t-1},e_{t+1})}\right] \times \\ \pi\left(m_t=1 | e_{t-1}, e_{t+1}\right) \end{array}\right\}^{c\left(e_{t-1}, 0, e_{t+1}, 1\right)}
\end{aligned}
$$

where $c\left(e_{t-1}, e_t, e_{t+1}, m_t\right)$ are the incomplete counts in the missing-data sample. Combining the two likelihood functions shows that there are three free parameters in the missing-data likelihood function but only enough information to estimate two. Assuming MAR constrains all three parameters. Assuming $\delta(m_t$

$|e_{t-1}, e_t, e_{t+1}) = 1$ for one base group permits estimation of the other δs since they are constrained such that

$$\pi\left(e_t = 0|e_{t-1}, e_{t+1}, m_t\right) + \pi\left(e_t = 1|e_{t-1}, e_{t+1}, m_t\right) = 1$$

for $m_t = 0, 1$.

Bayesian Estimation

We use a Dirichlet prior on $\pi\left(e_{t-1}, e_t, e_{t+1}, m_t\right)$, called $\alpha\left(e_{t-1}, e_t, e_{t+1}, m_t\right)$. We estimate the posterior distribution

$$\pi\left(e_{t-1}, e_t, e_{t+1}, m_t|\alpha\left(e_{t-1}, e_t, e_{t+1}, m_t\right)\right)$$

and sample from $\alpha\left(e_{t-1}, e_t, e_{t+1}, m_t\right)$, inserting this value into

$$\pi\left(e_{t-1}, e_t, e_{t+1}, m_t|\alpha\left(e_{t-1}, e_t, e_{t+1}, m_t\right)\right).$$

Next, we compute

$$\pi(e_t|e_{t-1}, e_{t+1}, m_t = 1|\alpha\left(e_{t-1}, e_t, e_{t+1}, m_t\right))$$

and impute missing employment state e_t with this probability.

Simpler Likelihood

We implement a simpler likelihood function using the notation

$$\pi = \Pr\left[e_t = 1|e_{t-1}, e_{t+1}\right]$$

and

$$\xi = \Pr\left[m_t = 0|e_t = 1, e_{t-1}, e_{t+1}\right].$$

The incomplete sample consists of selecting a PIK-SEIN pair for the quarter t from the ones with the correct configuration of $\left(e_{t-1}, e_{t+1}\right)$. Then, the latent employment state is realized. If $e_t = 1$, then the record is retained with probability ξ. If the latent employment state is $e_t = 0$, it is never retained. In the complete data sample, every PIK-SEIN pair for quarter t has its employment state correctly recorded as either 0 or 1.

Counts are defined by

$$c = \text{count of } e_t = 1 \text{ in complete data, given } (e_{t-1}, e_{t+1})$$

$$n = \text{count of PIK-SEINs in completed data, given } (e_{t-1}, e_{t+1})$$

$$x = \text{count of } e_t = 1 \text{ in incompleted data, given } (e_{t-1}, e_{t+1})$$

$$r = \text{count of PIK-SEINs in incompleted data, given } (e_{t-1}, e_{t+1})$$

and the likelihood function is

$$\ln \pounds = const + x \ln(\pi\xi) + (r - x)\ln(1 - \pi\xi) + c\ln(\pi) + (n - c)\ln(\pi).$$

Hence, the maximum likelihood estimators are

$$\hat{\pi} = \frac{c}{n}$$

and

$$\hat{\xi} = \frac{x/r}{c/n},$$

with first order conditions

$$\frac{x}{\xi} = \frac{\pi(r - x)}{1 - \pi\xi}$$

and

$$\frac{(x + c)}{\pi} = \frac{\xi(r - x)}{1 - \pi\xi} + \frac{(n - c)}{1 - \pi}.$$

So the probability required for imputing the missing employment state data is

$$\Pr[e_t = 1 | m_t = 1] = \frac{\pi(1 - \xi)}{\pi(1 - \xi) + (1 - \pi)}$$

Because of the structure of the problem, the natural conjugate prior for proportions (Dirichlet) does not work here exactly. Instead, we use the Dirichlet prior on π and ξ. Since the complete data sample contains all the information about the parameter π, we use the prior $D(\alpha_0, \alpha_1)$ for $(1-\pi)$ and π, respectively, so that $\pi \sim D(n-c+\alpha_0, c+\alpha_1)$. We draw π from this posterior using equal, small values for α_0, α_1. Next, we sample from the asymptotic approximation to the posterior of ξ, namely, $\xi \sim N\left(\hat{\xi}, \frac{\hat{\xi}(1-\hat{\xi})}{r}\right)$. Given the two draws, we evaluate $\Pr[e_t = 1 | m_t = 1]$ once for each (e_{t-1}, e_{t+1}) group, then for every PIK-SEIN match with $e_t \neq 1$ (the incompletely observed cases) we assign a random uniform number. A missing data implicate is generated if the random uniform number assigned to the PIK-SEIN match is less than the probability $p = \Pr[e_t = 1 | m_t = 1]$ for that $(e_{t-1}\ , e_{t+1})$ group.

3.1.3 Imputing Missing Earnings

The corresponding values of earnings for those with imputed jobs are determined using the method of Sequential Regression Multiple Imputation (SRMI) based on a Kernel Density Estimator (KDE) developed by Woodcock and Benedetto (2006). Two quarters of complete data are appended to the incomplete data quarter for the purpose of training the model.[7] Initially, a Bayesian bootstrapping method is used to fill missing earnings with values from a set of candidates within specified by-groups. These by-groups (By) and their covariates (X) for the second stage

[7]All states except Illinois append 3-quarter windows from one year ahead and one year behind the missing data quarter. Illinois has two 7-quarter windows appended from two and three years ahead of 1993q1 to patch the two holes that are one year apart.

imputation are defined as follows:

Groups:	G1	G1	G2	G2	G3	G3	G4	G4
Type:	By	X	By	X	By	X	By	X
nojob_1t	0	0	1	0	1	0	1	0
nojob_t1	0	0	1	0	1	0	1	0
male	1	0	1	0	1	0	1	0
sic_division	1	0	1	0	1	0	0	1
agecat	1	0	1	0	0	1	0	1
decile_1t	1	0	0	1	0	1	0	1
nonwhite	1	0	0	1	0	1	0	1
decile_t1	1	0	0	1	0	1	0	1
earn_1t	0	1	0	1	0	1	0	1
earn_t1	0	1	0	1	0	1	0	1
pikavg_1t	0	1	0	1	0	1	0	1
indpik_1t	0	1	0	1	0	1	0	1
seinavg_1t	0	1	0	1	0	1	0	1
indsein_1t	0	1	0	1	0	1	0	1
pikavg_t1	0	1	0	1	0	1	0	1
indpik_t1	0	1	0	1	0	1	0	1
seinavg_t1	0	1	0	1	0	1	0	1
indsein_t1	0	1	0	1	0	1	0	1

Variables that are used in this method are described below.

nojob_1t	- 1 if no job was held (previous quarter), 0 otherwise
nojob_t1	- 1 if no job is held (subsequent quarter), 0 otherwise
male	- 1 if male, 0 if female
sic_division	- categorical variable for SIC division
agecat	- categorical age variable
decile_1t	- categorical decile variable (previous quarter)
nonwhite	- 1 if nonwhite, 0 if white
decile_t1	- categorical decile variable (subsequent quarter)
earn_1t	- logarithm of earnings (previous quarter)
earn_t1	- logarithm of earnings (subsequent quarter)
pikavg_1t	- PIK average earnings across all jobs (previous quarter)
indpik_1t	- 1 if *pikavg_1t* is 0, 0 otherwise
seinavg_1t	- SEIN average earnings across all people (previous quarter)
indsein_1t	- 1 if *seinavg_1t* is 0, 0 otherwise
pikavg_t1	- PIK average earnings across all jobs (subsequent quarter)
indpik_t1	- 1 if *pikavg_t1* is 0, 0 otherwise
seinavg_t1	- SEIN average earnings across all people (subsequent quarter)
indsein_t1	- 1 if *seinavg_t1* is 0, 0 otherwise

Earnings deciles are defined by quarter for the two quarters surrounding the missing data (*decile*) and 3-quarter work patterns are accounted for (*nojob*). The specified age categories (*agecat*) are 0-16, 17-21, 22-24, 25-34, 35-44, 45-54, 55-64, and 65+ years, because the graph of the age of employed individuals in the Current Population Survey in Figure 3.1.3 lends itself to these bins. The following SIC Divisions (*sic_division*) are defined: Agriculture, Mining, Construction, Manufacturing, Transportation and Utilities, Wholesale Trade, Retail Trade, FIRE, Services, Public Administration, and Other. Average earnings across all jobs for each person (*pikavg*) and SEIN (*seinavg*) are included for the bordering quarters, as is an indicator when these values are zero (*indpik* and *indsein*). All categorical covariates become indicator variables in the second stage imputation. Cells with fewer than 100 records are passed into the next grouping.

3.1.4 Improved Files and the Data Snapshot

Tables 3.10- 3.14 illustrate the effectiveness of the quarterly job imputation by overall employment rates, while Tables 3.15- 3.19 do the same for the wage imputation. A closer examination of the earnings imputation by deciles of the distribution are outlined in Tables 3.20- 3.24 for the completed data, the input data, and the combined data in the overall sample and by 3-quarter work patterns. Earnings statistics in this last set of tables are for all data in the quarter together (ernQQ), for the originally complete data (ernQQ_c), for the completed but originally missing data (ernQQ_i). They are also broken down by 3-quarter work patterns using these categories: Work-MissingWork-Work (WMW), Work-MissingWork-NoWork (WMN), NoWork-MissingWork-Work (NMW), and NoWork-MissingWork-NoWork (NMN).

The resulting improved EHFs are entered into the production development environment so that the complete family of EHFs and ECFs can be constructed for these states. The improved sets of EHFs and ECFs are integrated into the data snapshot so that the files used for this project will remain stable during the course of this research while the production environment continues to be regularly updated.

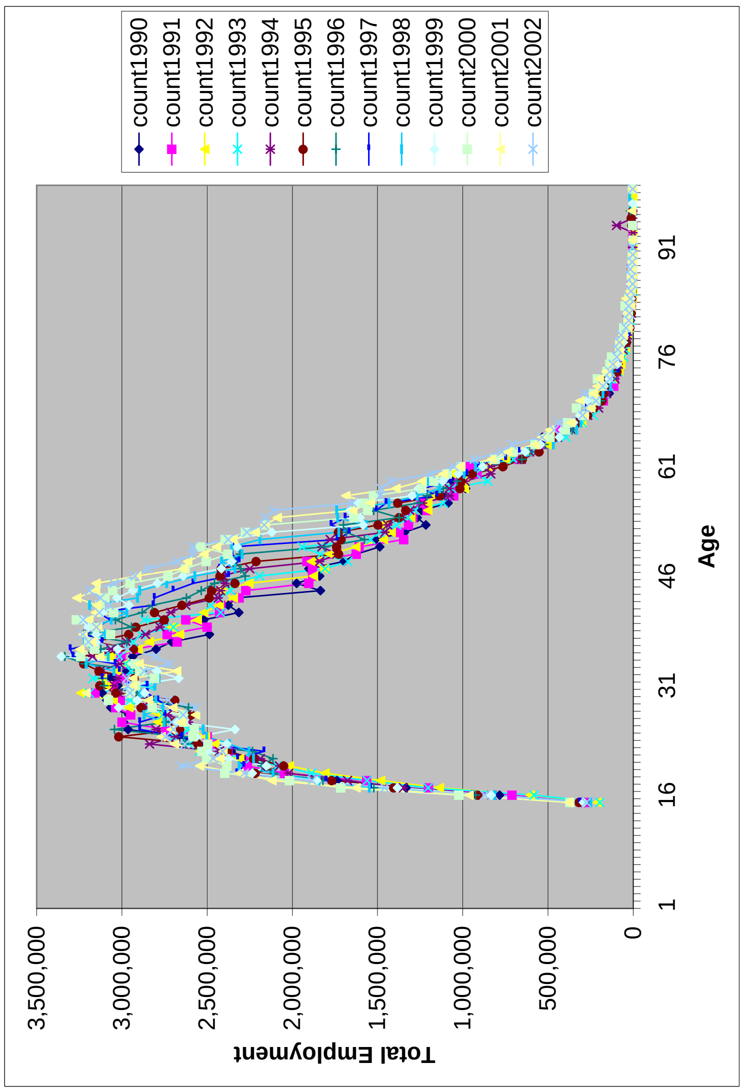

Figure 3.2: Age Distribution of Employed Individuals

Table 3.10: Colorado Employment Counts

Year	**Qtr**	**B Old**	**B**	**BLS emp-month1**	**ES202 emp-month1**
1990	1	-	-	1,201,304	1,201,239
1990	2	1,157,897	1,157,897	1,216,552	1,216,408
1990	3	1,125,350	1,125,350	1,257,849	1,257,852
1990	4	638,003	638,003	1,244,986	1,244,986
1991	1	1,312,463	1,312,463	1,229,041	1,229,060
1991	2	1,343,206	1,343,206	1,235,403	1,235,007
1991	3	1,374,379	1,374,379	1,271,347	1,270,691
1991	4	1,261,220	1,261,220	1,260,622	1,260,644
1992	1	1,257,164	1,257,164	1,253,733	1,253,733
1992	2	1,410,868	1,410,868	1,276,101	1,276,101
1992	3	1,452,261	1,452,261	1,325,614	1,324,062
1992	4	1,438,682	1,438,682	1,317,370	1,317,370
1993	1	**84,882**	**1,421,195**	1,311,904	1,311,640
1993	2	**96,153**	**1,496,831**	1,344,589	1,344,589
1993	3	1,525,766	1,525,766	1,393,134	1,393,228
1993	4	1,489,845	1,489,845	1,387,399	1,387,399
1994	1	1,453,967	1,453,967	1,388,976	1,388,977
1994	2	1,485,353	1,485,353	1,420,380	1,420,380
1994	3	1,506,524	1,506,524	1,475,458	1,475,458
1994	4	1,474,157	1,474,157	1,467,445	1,467,540
1995	1	1,471,428	1,471,428	1,467,372	1,467,372
1995	2	1,516,192	1,516,192	1,491,306	1,491,306
1995	3	1,554,323	1,554,323	1,540,903	1,540,903
1995	4	1,546,770	1,546,770	1,532,673	1,532,506
1996	1	1,545,614	1,545,614	1,525,744	1,525,744
1996	2	1,679,342	1,679,342	1,552,937	1,552,937
1996	3	1,729,485	1,729,485	1,604,562	1,604,562
1996	4	1,711,476	1,711,476	1,592,111	1,592,111
1997	1	1,659,476	1,659,476	1,590,279	1,590,279
1997	2	1,679,075	1,679,075	1,624,808	1,624,829
1997	3	1,659,233	1,659,233	1,682,028	1,682,816
1997	4	1,584,054	1,584,054	1,674,335	1,674,239
1998	1	1,572,755	1,572,755	1,667,972	1,667,903
1998	2	1,672,603	1,672,603	1,695,621	1,695,236
1998	3	1,696,867	1,696,867	1,757,771	1,757,576
1998	4	1,665,780	1,665,780	1,743,551	1,743,158
1999	1	1,628,108	1,628,108	1,734,939	1,734,847
1999	2	1,734,650	1,734,650	1,770,692	1,770,692
1999	3	1,776,261	1,776,261	1,826,000	1,826,001
1999	4	1,766,513	1,766,513	1,808,507	1,807,900
2000	1	1,780,714	1,780,714	1,796,890	1,797,329
2000	2	1,875,649	1,875,649	1,835,728	1,835,665
2000	3	1,921,144	1,921,144	1,900,115	1,900,101
2000	4	1,837,789	1,837,789	1,885,632	1,885,671
2001	1	1,812,912	1,812,912	1,865,196	1,865,196
2001	2	1,957,346	1,957,346	1,875,017	1,874,831
2001	3	1,977,937	1,977,937	1,904,270	1,904,260
2001	4	1,883,623	1,883,623	1,843,969	1,843,921
2002	1	1,804,505	1,804,505	1,789,392	1,789,349
2002	2	1,861,130	1,861,130	1,810,487	1,810,419
2002	3	1,890,835	1,890,835	1,842,622	1,842,608
2002	4	1,874,523	1,874,523	1,800,873	1,800,322
2003	1	1,790,716	1,790,716	1,759,305	1,758,447
2003	2	1,797,353	1,797,353	1,759,265	1,759,386
2003	3	1,848,700	1,848,700	1,799,680	1,799,680
2003	4	1,888,618	1,888,618	1,777,371	1,777,333
2004	1	1,860,738	1,860,738	1,750,306	1,750,908

Table 3.11: Illinois Employment Counts

Year	Qtr	B Old	B	BLS emp-month1	ES202 emp-month1
1990	1	-	-	4,345,291	4,357,028
1990	2	4,409,874	4,409,874	4,413,148	4,419,893
1990	3	4,746,595	4,746,595	4,526,937	4,531,231
1990	4	4,588,349	4,588,349	4,485,882	4,495,279
1991	1	4,464,664	4,464,664	4,321,107	4,323,423
1991	2	4,466,004	4,466,004	4,366,343	4,368,524
1991	3	4,421,712	4,421,712	4,447,930	4,458,102
1991	4	4,205,686	4,205,686	4,406,956	4,428,147
1992	1	**3,851,760**	**4,304,359**	4,251,991	4,265,733
1992	2	**4,025,021**	**4,445,188**	4,327,971	4,338,444
1992	3	4,575,235	4,575,235	4,440,244	4,457,385
1992	4	4,529,907	4,529,907	4,451,135	4,462,633
1993	1	**3,797,985**	**4,502,603**	4,315,656	4,328,907
1993	2	**3,902,765**	**4,609,002**	4,420,987	4,427,366
1993	3	4,779,554	4,779,554	4,527,060	4,532,898
1993	4	4,949,507	4,949,507	4,561,584	4,562,851
1994	1	4,911,607	4,911,607	4,431,817	4,433,307
1994	2	5,001,620	5,001,620	4,558,054	4,560,440
1994	3	5,133,884	5,133,884	4,674,684	4,674,817
1994	4	5,153,319	5,153,319	4,663,230	4,666,552
1995	1	5,075,823	5,075,823	4,569,153	4,570,331
1995	2	5,172,059	5,172,059	4,670,631	4,667,744
1995	3	5,274,083	5,274,083	4,758,961	4,761,530
1995	4	5,271,528	5,271,528	4,773,732	4,773,345
1996	1	5,168,217	5,168,217	4,657,943	4,656,597
1996	2	5,249,318	5,249,318	4,734,181	4,732,396
1996	3	5,375,210	5,375,210	4,839,577	4,835,141
1996	4	5,349,673	5,349,673	4,854,173	4,849,398
1997	1	5,223,451	5,223,451	4,722,643	4,720,362
1997	2	5,354,853	5,354,853	4,840,237	4,836,835
1997	3	5,437,141	5,437,141	4,937,897	4,932,407
1997	4	5,445,737	5,445,737	4,959,198	4,957,176
1998	1	5,365,661	5,365,661	4,845,563	4,844,146
1998	2	5,443,817	5,443,817	4,948,458	4,950,038
1998	3	5,571,917	5,571,917	5,060,902	5,060,661
1998	4	5,561,516	5,561,516	5,073,756	5,071,412
1999	1	5,413,929	5,413,929	4,897,891	4,899,867
1999	2	5,558,626	5,558,626	5,025,210	5,028,338
1999	3	5,667,976	5,667,976	5,114,699	5,114,002
1999	4	5,643,039	5,643,039	5,118,835	5,118,578
2000	1	5,542,242	5,542,242	4,986,499	4,991,762
2000	2	5,587,155	5,587,155	5,112,284	5,110,886
2000	3	5,728,864	5,728,864	5,191,404	5,186,936
2000	4	5,753,793	5,753,793	5,181,136	5,176,157
2001	1	5,574,088	5,574,088	5,010,787	5,009,801
2001	2	5,649,306	5,649,306	5,087,322	5,086,596
2001	3	5,751,458	5,751,458	5,124,813	5,125,342
2001	4	5,652,080	5,652,080	5,051,630	5,053,414
2002	1	5,465,920	5,465,920	4,861,144	4,860,455
2002	2	5,548,356	5,548,356	4,930,779	4,930,476
2002	3	5,645,193	5,645,193	4,998,610	4,997,554
2002	4	5,573,864	5,573,864	4,977,700	4,974,890
2003	1	5,419,730	5,419,730	4,797,592	4,801,803
2003	2	5,424,724	5,424,724	4,859,187	4,861,631
2003	3	5,506,160	5,506,160	4,925,963	4,925,091
2003	4	5,507,480	5,507,480	4,916,868	4,919,946
2004	1	5,376,517	5,362,185	4,757,126	4,769,070

Table 3.12: Kansas Employment Counts

Year	Qtr	B Old	B	BLS emp-month1	ES202 emp-month1
1990	1	-	-	834,114	835,867
1990	2	100,230	100,230	857,323	857,588
1990	3	982,621	982,621	872,733	871,953
1990	4	989,699	989,699	865,591	867,548
1991	1	971,043	971,043	835,438	835,790
1991	2	992,905	992,905	857,163	857,440
1991	3	1,001,487	1,001,487	877,229	876,717
1991	4	992,608	992,608	873,194	873,268
1992	1	984,238	984,238	854,307	854,468
1992	2	999,789	999,789	876,209	876,093
1992	3	1,018,818	1,018,818	888,627	888,622
1992	4	**689,066**	**1,000,629**	884,517	883,722
1993	1	**672,827**	**993,688**	859,291	860,194
1993	2	979,142	979,142	888,167	888,013
1993	3	990,153	990,153	902,850	902,325
1993	4	1,011,059	1,011,059	899,463	900,141
1994	1	1,015,369	1,015,369	882,690	882,742
1994	2	1,039,207	1,039,207	910,627	911,125
1994	3	1,045,739	1,045,739	933,570	932,773
1994	4	1,050,244	1,050,244	930,074	930,240
1995	1	1,053,444	1,053,444	916,874	917,025
1995	2	1,074,725	1,074,725	940,259	940,439
1995	3	1,081,375	1,081,375	955,796	955,796
1995	4	1,072,507	1,072,507	959,085	959,086
1996	1	1,071,059	1,071,059	943,279	943,428
1996	2	1,104,789	1,104,789	973,815	973,909
1996	3	1,123,904	1,123,904	990,062	990,426
1996	4	1,114,335	1,114,335	990,054	990,026
1997	1	1,083,254	1,083,254	974,386	972,625
1997	2	1,118,071	1,118,071	1,008,793	1,009,106
1997	3	1,135,883	1,135,883	1,038,765	1,033,266
1997	4	1,136,754	1,136,754	1,031,821	1,032,162
1998	1	1,139,308	1,139,308	1,023,198	1,022,668
1998	2	1,174,344	1,174,344	1,052,537	1,054,824
1998	3	1,184,092	1,184,092	1,069,836	1,070,745
1998	4	1,158,118	1,158,118	1,069,798	1,070,863
1999	1	1,151,962	1,151,962	1,040,022	1,042,301
1999	2	1,191,008	1,191,008	1,069,003	1,069,049
1999	3	1,209,192	1,209,192	1,087,269	1,088,235
1999	4	1,201,526	1,201,526	1,078,284	1,078,963
2000	1	1,188,913	1,188,913	1,056,644	1,058,638
2000	2	1,219,972	1,219,972	1,081,298	1,083,244
2000	3	1,234,420	1,234,420	1,091,938	1,076,522
2000	4	1,221,966	1,221,966	1,091,637	1,090,651
2001	1	1,208,116	1,208,116	1,070,813	1,068,082
2001	2	1,228,214	1,228,214	1,084,222	1,087,311
2001	3	1,247,393	1,247,393	1,091,085	1,091,516
2001	4	1,229,409	1,229,409	1,080,222	1,081,404
2002	1	1,188,088	1,188,088	1,048,467	1,046,831
2002	2	1,201,385	1,201,385	1,068,652	1,068,841
2002	3	1,203,904	1,203,904	1,071,786	1,072,190
2002	4	1,197,326	1,197,326	1,061,311	1,061,172
2003	1	1,179,958	1,179,958	1,033,292	1,033,183
2003	2	1,187,140	1,187,140	1,045,763	1,046,764
2003	3	1,196,047	1,196,047	1,054,183	1,055,303
2003	4	1,186,229	1,186,229	1,054,155	1,054,322
2004	1	1,180,309	1,180,309	1,027,886	1,030,113

Table 3.13: Missouri Employment Counts

Year	**Qtr**	**B Old**	**B**	**BLS emp-month1**	**ES202 emp-month1**
1990	1	-	-	1,886,092	1,886,299
1990	2	2,126,347	2,126,347	1,910,483	1,921,535
1990	3	2,174,774	2,174,774	1,959,014	1,958,679
1990	4	2,151,825	2,151,825	1,946,452	1,945,168
1991	1	2,083,595	2,083,595	1,838,627	1,837,978
1991	2	2,108,942	2,108,942	1,875,522	1,870,240
1991	3	2,148,910	2,148,910	1,918,311	1,916,897
1991	4	2,136,249	2,136,249	1,911,280	1,908,826
1992	1	2,098,160	2,098,160	1,844,041	1,841,380
1992	2	2,131,764	2,131,764	1,901,119	1,899,489
1992	3	2,179,320	2,179,320	1,947,214	1,946,814
1992	4	2,162,574	2,162,574	1,942,566	1,941,849
1993	1	2,120,331	2,120,331	1,874,743	1,869,597
1993	2	2,160,063	2,160,063	1,944,275	1,943,435
1993	3	2,216,332	2,216,332	2,000,624	1,998,122
1993	4	2,212,933	2,212,933	2,001,994	2,001,140
1994	1	2,171,994	2,171,994	1,932,249	1,917,035
1994	2	2,227,358	2,227,358	2,007,518	2,007,577
1994	3	2,289,932	2,289,932	2,067,739	2,063,561
1994	4	**1,560,136**	**2,303,435**	2,070,921	2,068,520
1995	1	**1,553,789**	**2,265,239**	2,004,301	2,002,542
1995	2	2,313,899	2,313,899	2,072,659	2,071,253
1995	3	2,357,215	2,357,215	2,100,898	2,099,336
1995	4	2,350,592	2,350,592	2,096,053	2,094,249
1996	1	2,308,453	2,308,453	2,038,484	2,033,214
1996	2	2,345,056	2,345,056	2,103,209	2,110,754
1996	3	2,400,490	2,400,490	2,139,857	2,137,080
1996	4	2,392,740	2,392,740	2,142,854	2,143,357
1997	1	2,350,909	2,350,909	2,091,520	2,090,869
1997	2	2,403,346	2,403,346	2,160,292	2,160,503
1997	3	2,449,115	2,449,115	2,194,513	2,187,959
1997	4	2,440,603	2,440,603	2,199,359	2,200,060
1998	1	2,389,374	2,389,374	2,137,600	2,141,295
1998	2	2,449,098	2,449,098	2,205,826	2,206,121
1998	3	2,494,448	2,494,448	2,240,775	2,241,009
1998	4	2,485,430	2,485,430	2,233,347	2,233,111
1999	1	2,434,018	2,434,018	2,162,069	2,163,359
1999	2	2,495,262	2,495,262	2,241,019	2,250,039
1999	3	2,540,946	2,540,946	2,286,245	2,288,189
1999	4	2,516,871	2,516,871	2,270,190	2,272,687
2000	1	2,467,139	2,467,139	2,211,419	2,728,061
2000	2	2,534,217	2,534,217	2,266,477	2,285,700
2000	3	2,586,649	2,586,649	2,293,956	2,294,404
2000	4	2,560,986	2,560,986	2,286,170	2,287,241
2001	1	2,501,215	2,501,215	2,200,533	2,206,454
2001	2	2,519,320	2,519,320	2,255,096	2,257,522
2001	3	2,574,185	2,574,185	2,257,788	2,456,806
2001	4	2,542,910	2,542,910	2,234,021	2,234,992
2002	1	2,467,949	2,467,949	2,154,866	2,159,129
2002	2	2,501,904	2,501,904	2,215,943	2,225,952
2002	3	2,515,920	2,515,920	2,233,768	2,422,222
2002	4	2,528,005	2,528,005	2,229,679	2,230,539
2003	1	2,470,841	2,470,841	2,151,676	3,033,558
2003	2	2,493,877	2,493,877	2,200,666	2,202,705
2003	3	2,531,783	2,531,783	2,218,305	2,221,766
2003	4	2,510,864	2,510,864	2,216,682	2,219,901
2004	1	2,475,499	2,474,778	2,147,039	2,147,658

Table 3.14: Pennsylvania Employment Counts

Year	Qtr	B Old	B	BLS emp-month1	ES202 emp-month1
1991	1	-	-	4,236,384	4,236,387
1991	2	4,700,421	4,700,421	4,260,573	4,260,573
1991	3	4,740,728	4,740,728	4,301,906	4,301,912
1991	4	4,715,342	4,715,342	4,302,957	4,302,957
1992	1	4,557,108	4,557,108	4,184,916	4,185,342
1992	2	4,568,454	4,568,454	4,241,545	4,241,545
1992	3	4,723,189	4,723,189	4,321,835	4,324,171
1992	4	4,667,552	4,667,552	4,325,707	4,325,707
1993	1	4,591,299	4,591,299	4,213,771	4,213,793
1993	2	4,678,551	4,678,551	4,268,291	4,268,307
1993	3	4,789,488	4,789,488	4,356,371	4,356,371
1993	4	4,735,962	4,735,962	4,360,714	4,360,708
1994	1	4,692,261	4,692,261	4,223,657	4,223,657
1994	2	4,752,467	4,752,467	4,325,274	4,324,485
1994	3	4,881,056	4,881,056	4,424,191	4,424,192
1994	4	4,870,482	4,870,482	4,429,051	4,429,040
1995	1	4,812,641	4,812,641	4,313,588	4,314,170
1995	2	4,866,324	4,866,324	4,387,664	4,387,666
1995	3	4,954,273	4,954,273	4,456,120	4,456,120
1995	4	4,910,658	4,910,658	4,469,761	4,469,761
1996	1	4,814,158	4,814,158	4,308,551	4,308,551
1996	2	4,899,310	4,899,310	4,439,076	4,439,076
1996	3	5,013,767	5,013,767	4,527,102	4,527,972
1996	4	**49,521**	**4,969,278**	4,540,496	4,540,295
1997	1	**48,761**	**4,894,815**	4,446,930	4,446,855
1997	2	4,979,119	4,979,119	4,529,710	-
1997	3	5,040,479	5,040,479	4,642,906	-
1997	4	5,045,693	5,045,693	4,649,604	-
1998	1	4,996,604	4,996,604	4,556,245	4,556,949
1998	2	5,065,184	5,065,184	4,644,391	4,646,497
1998	3	5,135,585	5,135,585	4,731,739	4,734,744
1998	4	5,113,798	5,113,798	4,735,829	4,736,542
1999	1	5,012,308	5,012,308	4,623,145	4,623,304
1999	2	5,084,835	5,084,835	4,739,220	4,755,171
1999	3	5,100,130	5,100,130	4,850,143	4,826,016
1999	4	5,054,886	5,054,886	4,818,516	4,815,739
2000	1	5,048,672	5,048,672	4,723,295	4,722,007
2000	2	5,126,968	5,126,968	4,831,492	4,830,724
2000	3	5,185,512	5,185,512	4,917,413	4,916,750
2000	4	5,160,268	5,160,268	4,898,758	4,897,023
2001	1	5,091,076	5,091,076	4,790,531	4,790,728
2001	2	5,137,627	5,137,627	4,842,480	4,841,770
2001	3	5,211,680	5,211,680	4,884,529	4,883,439
2001	4	4,979,337	4,979,337	4,837,252	4,834,399
2002	1	4,877,230	4,877,230	4,700,448	4,700,410
2002	2	5,133,137	5,133,137	4,767,392	4,767,479
2002	3	5,192,404	5,192,404	4,840,014	4,838,554
2002	4	5,123,995	5,123,995	4,811,525	4,811,580
2003	1	4,952,668	4,952,668	4,671,499	4,693,887
2003	2	4,853,937	4,853,937	4,725,018	4,735,958
2003	3	5,064,154	5,064,154	4,790,105	4,801,279
2003	4	5,040,599	5,040,599	4,786,728	4,793,206
2004	1	5,019,131	4,970,430	4,655,607	4,671,384

Table 3.15: Colorado CPI-deflated Wage Statistics

Year	Qtr	Observations	Mean of CPI-deflated Wage	Stdev of CPI-deflated Wage
1990	**1**	1,597,193	5,860	7,415
1990	**2**	1,609,701	5,899	7,230
1990	**3**	1,501,850	6,080	8,051
1990	**4**	1,731,769	6,490	8,475
1991	**1**	1,664,033	6,208	7,964
1991	**2**	1,753,370	6,017	8,027
1991	**3**	1,785,460	6,027	7,867
1991	**4**	1,600,908	6,698	9,908
1992	**1**	1,729,544	6,285	8,261
1992	**2**	1,838,260	6,002	8,008
1992	**3**	1,882,913	5,999	7,974
1992	**4**	1,851,487	6,687	10,573
1993	**1**	1,853,886	5,925	8,110
1993	**2**	1,945,841	5,900	7,894
1993	**3**	2,003,855	5,964	7,951
1993	**4**	1,928,883	6,614	10,580
1994	**1**	1,860,015	6,109	8,189
1994	**2**	1,972,056	5,866	8,027
1994	**3**	1,994,760	6,014	8,218
1994	**4**	1,961,362	6,462	10,182
1995	**1**	1,913,826	6,258	8,560
1995	**2**	2,022,211	5,897	8,103
1995	**3**	2,077,747	5,958	8,097
1995	**4**	2,038,057	6,521	10,077
1996	**1**	2,108,300	6,236	8,304
1996	**2**	2,243,518	5,889	8,039
1996	**3**	2,292,266	5,948	7,988
1996	**4**	2,232,101	6,524	9,844
1997	**1**	2,182,916	6,366	8,680
1997	**2**	2,283,105	6,069	8,181
1997	**3**	2,304,531	6,201	8,756
1997	**4**	2,170,188	6,889	10,296
1998	**1**	2,221,992	6,587	8,977
1998	**2**	2,344,978	6,262	8,352
1998	**3**	2,389,243	6,457	8,450
1998	**4**	2,281,911	7,265	10,787
1999	**1**	2,298,081	6,731	9,073
1999	**2**	2,436,013	6,484	8,751
1999	**3**	2,487,516	6,627	8,692
1999	**4**	2,434,380	7,387	10,890
2000	**1**	2,428,436	6,979	9,128
2000	**2**	2,567,671	6,736	8,776
2000	**3**	2,599,846	6,843	8,850
2000	**4**	2,456,836	7,574	10,597
2001	**1**	2,485,876	7,319	9,176
2001	**2**	2,600,273	7,021	8,781
2001	**3**	2,578,426	7,011	8,532
2001	**4**	2,399,061	7,665	10,043
2002	**1**	2,340,654	7,405	8,876
2002	**2**	2,417,509	7,110	8,495
2002	**3**	2,439,830	7,159	8,346
2002	**4**	2,355,944	7,729	9,701
2003	**1**	2,233,029	7,456	8,769
2003	**2**	2,315,760	7,200	8,385
2003	**3**	2,398,915	7,190	8,378
2003	**4**	2,354,303	7,702	9,517
2004	**1**	2,290,888	7,445	8,868

Table 3.16: Illinois CPI-deflated Wage Statistics

Year	Qtr	Observations	Mean of CPI-deflated Wage	Stdev of CPI-deflated Wage
1990	**1**	5,242,674	7,226	18,781
1990	**2**	5,867,788	6,936	15,617
1990	**3**	5,843,202	6,787	12,673
1990	**4**	5,632,893	7,879	24,983
1991	**1**	5,404,157	7,102	15,602
1991	**2**	5,580,533	6,958	12,469
1991	**3**	5,555,525	6,738	15,160
1991	**4**	5,363,261	7,719	26,285
1992	**1**	5,287,782	7,573	19,719
1992	**2**	5,564,979	7,042	15,131
1992	**3**	5,717,146	6,919	14,001
1992	**4**	5,567,141	8,296	32,741
1993	**1**	5,457,391	7,022	18,447
1993	**2**	5,768,550	6,971	12,903
1993	**3**	6,064,169	6,827	12,835
1993	**4**	6,037,120	8,058	28,395
1994	**1**	5,841,665	7,089	14,280
1994	**2**	6,178,254	6,862	12,731
1994	**3**	6,394,892	6,920	14,562
1994	**4**	6,280,657	7,720	22,704
1995	**1**	6,099,193	7,315	17,203
1995	**2**	6,362,159	6,902	16,394
1995	**3**	6,489,806	6,791	15,973
1995	**4**	6,377,226	7,752	24,860
1996	**1**	6,162,127	7,408	21,089
1996	**2**	6,449,665	6,980	16,383
1996	**3**	6,592,554	6,829	14,004
1996	**4**	6,478,038	7,871	24,103
1997	**1**	6,264,457	7,528	21,609
1997	**2**	6,586,554	7,110	18,495
1997	**3**	6,723,170	7,047	20,953
1997	**4**	6,653,394	8,158	27,572
1998	**1**	6,413,104	7,748	25,162
1998	**2**	6,735,524	7,366	22,509
1998	**3**	6,893,246	7,210	18,795
1998	**4**	6,795,467	8,504	29,970
1999	**1**	6,536,584	7,829	26,989
1999	**2**	6,895,798	7,480	22,178
1999	**3**	7,005,208	7,423	21,337
1999	**4**	6,912,687	8,656	31,020
2000	**1**	6,688,751	8,192	29,068
2000	**2**	6,970,388	7,538	22,650
2000	**3**	7,123,455	7,589	192,398
2000	**4**	6,950,121	8,620	51,639
2001	**1**	6,669,879	8,417	37,692
2001	**2**	6,920,874	7,640	20,824
2001	**3**	6,929,237	7,556	39,514
2001	**4**	6,689,325	8,596	50,506
2002	**1**	6,431,547	8,388	26,629
2002	**2**	6,690,549	7,805	21,519
2002	**3**	6,766,547	7,602	18,199
2002	**4**	6,598,788	8,577	24,913
2003	**1**	6,303,240	8,358	25,160
2003	**2**	6,491,994	7,783	19,779
2003	**3**	6,621,216	7,668	17,786
2003	**4**	6,495,805	8,712	27,982
2004	**1**	6,240,064	8,491	29,941

Table 3.17: Kansas CPI-deflated Wage Statistics

Year	Qtr	Observations	Mean of CPI-deflated Wage	Stdev of CPI-deflated Wage
1990	**1**	130,943	4,448	4,168
1990	**2**	1,223,191	5,525	7,846
1990	**3**	1,257,623	5,274	7,427
1990	**4**	1,217,234	6,016	11,034
1991	**1**	1,176,171	5,531	7,254
1991	**2**	1,240,231	5,488	7,409
1991	**3**	1,250,179	5,301	7,316
1991	**4**	1,202,793	6,067	10,844
1992	**1**	1,188,912	5,595	7,740
1992	**2**	1,251,604	5,543	7,744
1992	**3**	1,277,456	5,309	7,581
1992	**4**	1,233,094	6,181	12,688
1993	**1**	1,208,991	5,410	7,225
1993	**2**	1,290,468	5,467	7,526
1993	**3**	1,304,966	5,312	7,426
1993	**4**	1,270,387	6,109	11,582
1994	**1**	1,249,576	5,439	7,543
1994	**2**	1,329,407	5,417	7,271
1994	**3**	1,358,716	5,298	7,482
1994	**4**	1,331,276	5,864	10,186
1995	**1**	1,310,432	5,563	8,453
1995	**2**	1,375,000	5,440	7,808
1995	**3**	1,398,101	5,226	7,599
1995	**4**	1,365,224	5,966	11,117
1996	**1**	1,343,943	5,588	8,773
1996	**2**	1,416,572	5,485	7,917
1996	**3**	1,436,046	5,266	7,952
1996	**4**	1,406,657	5,990	11,881
1997	**1**	1,373,961	5,646	8,966
1997	**2**	1,464,793	5,523	7,960
1997	**3**	1,478,855	5,378	7,914
1997	**4**	1,460,321	6,197	11,259
1998	**1**	1,428,203	5,833	9,946
1998	**2**	1,518,799	5,791	10,523
1998	**3**	1,529,533	5,542	8,499
1998	**4**	1,490,549	6,430	11,452
1999	**1**	1,458,073	5,794	9,589
1999	**2**	1,531,796	5,807	8,734
1999	**3**	1,547,140	5,713	8,422
1999	**4**	1,508,880	6,618	12,780
2000	**1**	1,482,294	6,078	10,266
2000	**2**	1,556,642	5,895	9,549
2000	**3**	1,560,780	5,778	9,958
2000	**4**	1,523,058	6,421	11,933
2001	**1**	1,485,917	6,166	9,747
2001	**2**	1,554,206	5,955	8,227
2001	**3**	1,556,542	5,838	8,404
2001	**4**	1,494,737	6,491	11,319
2002	**1**	1,436,721	6,309	9,947
2002	**2**	1,495,479	6,070	8,615
2002	**3**	1,494,474	5,921	8,312
2002	**4**	1,450,253	6,571	10,933
2003	**1**	1,396,535	6,358	10,153
2003	**2**	1,453,776	6,095	8,611
2003	**3**	1,451,646	6,018	8,600
2003	**4**	1,430,594	6,651	10,902
2004	**1**	1,401,020	6,333	10,989

Table 3.18: Missouri CPI-deflated Wage Statistics

Year	Qtr	Observations	Mean of CPI-deflated Wage	Stdev of CPI-deflated Wage
1990	**1**	2,510,979	6,003	8,197
1990	**2**	2,642,204	5,887	7,768
1990	**3**	2,675,469	5,677	7,686
1990	**4**	2,583,562	6,313	9,971
1991	**1**	2,468,320	5,996	17,161
1991	**2**	2,599,836	5,884	9,322
1991	**3**	2,624,528	5,715	11,444
1991	**4**	2,546,528	6,464	16,662
1992	**1**	2,473,592	6,050	10,472
1992	**2**	2,616,487	5,911	9,518
1992	**3**	2,655,969	5,708	11,047
1992	**4**	2,596,354	6,733	28,776
1993	**1**	2,512,592	5,798	9,949
1993	**2**	2,694,014	5,820	10,490
1993	**3**	2,751,028	5,655	12,407
1993	**4**	2,707,700	6,583	18,742
1994	**1**	2,632,591	5,859	12,441
1994	**2**	2,823,199	5,774	12,050
1994	**3**	2,897,411	5,735	11,221
1994	**4**	2,842,196	6,337	16,022
1995	**1**	2,768,946	6,010	12,308
1995	**2**	2,931,755	5,858	13,970
1995	**3**	2,964,441	5,663	13,703
1995	**4**	2,904,544	6,360	15,691
1996	**1**	2,812,985	6,062	15,642
1996	**2**	2,972,465	5,896	14,108
1996	**3**	3,015,580	5,652	11,711
1996	**4**	2,961,466	6,452	18,173
1997	**1**	2,879,031	6,187	17,671
1997	**2**	3,040,660	5,973	16,229
1997	**3**	3,081,542	5,817	28,299
1997	**4**	3,016,519	6,645	21,128
1998	**1**	2,923,050	6,292	20,751
1998	**2**	3,097,912	6,156	18,502
1998	**3**	3,140,067	5,953	18,632
1998	**4**	3,082,160	6,838	18,081
1999	**1**	2,974,238	6,345	23,178
1999	**2**	3,158,365	6,235	19,937
1999	**3**	3,201,329	6,065	15,525
1999	**4**	3,147,344	6,916	20,659
2000	**1**	3,070,978	6,523	18,035
2000	**2**	3,221,527	6,315	25,975
2000	**3**	3,254,984	6,122	24,820
2000	**4**	3,146,068	6,867	26,659
2001	**1**	3,051,590	6,649	16,617
2001	**2**	3,181,106	6,358	15,556
2001	**3**	3,171,347	6,213	19,815
2001	**4**	3,070,679	6,980	24,695
2002	**1**	2,954,067	6,815	21,098
2002	**2**	3,082,516	6,489	15,521
2002	**3**	3,118,309	6,302	13,898
2002	**4**	3,023,516	7,002	19,165
2003	**1**	2,924,964	6,779	47,136
2003	**2**	3,051,768	6,538	17,054
2003	**3**	3,065,367	6,401	52,779
2003	**4**	3,006,621	7,032	19,638
2004	**1**	2,917,402	6,733	19,940

Table 3.19: Pennsylvania CPI-deflated Wage Statistics

Year	Qtr	Observations	Mean of CPI-deflated Wage	Stdev of CPI-deflated Wage
1991	**1**	5,436,604	6,514	7,989
1991	**2**	5,604,312	6,443	7,871
1991	**3**	5,667,034	6,347	7,799
1991	**4**	5,541,018	6,967	9,648
1992	**1**	5,281,990	6,637	8,252
1992	**2**	5,559,265	6,555	8,042
1992	**3**	5,630,342	6,426	7,871
1992	**4**	5,540,150	7,290	10,278
1993	**1**	5,378,681	6,384	7,878
1993	**2**	5,641,044	6,541	8,025
1993	**3**	5,714,165	6,451	7,968
1993	**4**	5,654,808	7,169	10,045
1994	**1**	5,463,931	6,518	8,227
1994	**2**	5,777,067	6,469	7,929
1994	**3**	5,902,169	6,525	8,060
1994	**4**	5,807,539	6,972	9,808
1995	**1**	5,662,638	6,672	8,650
1995	**2**	5,875,395	6,537	8,191
1995	**3**	5,949,845	6,358	8,118
1995	**4**	5,841,189	6,947	9,930
1996	**1**	5,683,172	6,680	8,910
1996	**2**	5,957,323	6,523	8,335
1996	**3**	6,054,729	6,320	8,175
1996	**4**	5,961,281	6,857	10,131
1997	**1**	5,793,285	6,737	9,052
1997	**2**	6,047,674	6,589	8,438
1997	**3**	6,142,822	6,449	8,443
1997	**4**	6,068,843	7,219	10,392
1998	**1**	5,899,513	6,830	9,369
1998	**2**	6,181,049	6,721	8,785
1998	**3**	6,261,459	6,606	8,615
1998	**4**	6,190,822	7,450	10,597
1999	**1**	5,977,942	6,805	9,482
1999	**2**	6,241,231	6,792	8,922
1999	**3**	6,310,717	6,728	8,921
1999	**4**	6,257,004	7,545	10,751
2000	**1**	6,112,002	7,100	9,882
2000	**2**	6,383,321	6,796	8,914
2000	**3**	6,400,193	6,751	8,915
2000	**4**	6,326,369	7,361	10,491
2001	**1**	6,113,799	7,195	9,936
2001	**2**	6,313,148	6,895	8,813
2001	**3**	6,279,665	6,820	8,803
2001	**4**	5,934,952	7,429	10,306
2002	**1**	6,013,969	7,305	9,861
2002	**2**	6,206,390	7,085	9,275
2002	**3**	6,315,294	6,906	8,750
2002	**4**	6,129,869	7,509	10,221
2003	**1**	5,800,028	7,360	9,982
2003	**2**	6,010,992	7,119	8,219
2003	**3**	6,158,147	6,962	8,128
2003	**4**	6,091,831	7,648	10,454
2004	**1**	5,840,711	7,361	10,258

Table 3.20: Colorado Earnings Percentiles

Variable	N	Mean	1st Pctl	5th Ptcl	25th Pctl	50th Pctl	75th Pctl	95th Pctl	99th Pctl
ern33	3,589,559	5,192	30	124	1,172	3,625	6,985	14,698	29,008
ern33_c	1,853,886	4,972	27	103	970	3,327	6,743	14,455	28,383
ern33_i	1,731,149	5,054	27	102	957	3,361	6,874	14,712	29,064
wmwern33	2,318,500	6,589	138	615	2,759	5,118	8,392	16,321	31,926
wmwern33_c	1,214,488	6,456	125	571	2,604	4,947	8,302	16,163	31,266
wmwern33_i	1,144,723	6,551	124	565	2,612	5,022	8,438	16,423	32,010
wmnern33	392,631	2,537	17	51	326	1,071	2,891	9,091	21,391
wmnern33_c	206,707	2,140	14	37	225	768	2,282	8,041	20,075
wmnern33_i	191,590	2,137	14	37	216	736	2,236	8,176	20,427
nmwern33	577,721	3,205	30	96	543	1,612	4,077	10,576	21,244
nmwern33_c	282,343	2,228	22	62	321	942	2,597	8,037	16,563
nmwern33_i	255,955	2,150	21	59	300	871	2,388	7,996	16,939
nmnern33	300,707	1,696	13	28	126	416	1,320	6,333	18,715
nmnern33_c	150,348	2,031	14	30	149	498	1,654	7,354	24,666
nmnern33_i	138,881	2,095	14	30	150	499	1,679	7,603	26,431

Table 3.21: Illinois Earnings Percentiles

Variable	N	Mean	1st Pctl	5th Ptcl	25th Pctl	50th Pctl	75th Pctl	95th Pctl	99th Pctl
ern29	17,832,711	3,701	0	0	0	1,079	5,444	13,139	25,869
ern29_c	5,737,720	6,222	40	179	1,638	4,441	7,997	15,942	34,439
ern29_i	471,837	7,629	33	128	1,426	4,328	8,380	19,579	56,498
wmwern29	8,195,860	6,990	138	600	2,735	5,328	8,796	17,121	35,197
wmwern29_c	4,123,810	7,135	101	528	2,697	5,322	8,767	17,068	37,140
wmwern29_i	418,477	8,059	33	129	1,528	4,552	8,707	20,696	61,704
wmnern29	1,180,430	3,004	18	54	333	1,188	3,561	10,396	22,385
wmnern29_c	568,457	3,729	22	64	440	1,621	4,641	11,981	25,871
wmnern29_i	34,147	4,571	41	153	1,148	3,263	6,374	12,463	21,654
nmwern29	1,271,797	3,294	29	90	495	1,461	3,981	11,170	23,519
nmwern29_c	743,569	4,697	34	121	737	2,535	6,314	13,767	28,050
nmwern29_i	1,701	4,437	26	100	853	2,630	5,745	12,617	30,465
nmnern29	597,735	1,631	12	30	120	378	1,200	6,243	14,888
nmnern29_c	301,884	2,212	14	34	158	562	2,155	8,758	18,299
nmnern29_i	17,512	3,621	28	88	645	2,228	5,150	11,123	18,878

Table 3.21 (Continued)

Variable	**N**	**Mean**	**1st Pctl**	**5th Ptcl**	**25th Pctl**	**50th Pctl**	**75th Pctl**	**95th Pctl**	**99th Pctl**
ern33	17,651,541	3,739	0	0	0	1,144	5,500	13,195	26,000
ern33_c	5,717,680	5,926	35	150	1,445	4,151	7,751	15,841	33,370
ern33_i	842,656	5,815	26	80	837	3,320	7,318	16,153	37,687
wmwern33	8,195,860	6,990	138	600	2,735	5,328	8,796	17,121	35,197
wmwern33_c	4,184,868	6,934	72	432	2,541	5,175	8,667	17,115	36,852
wmwern33_i	616,607	6,965	28	90	1,266	4,400	8,538	18,205	44,945
wmnern33	1,180,430	3,004	18	54	333	1,188	3,561	10,396	22,385
wmnern33_c	562,489	3,410	19	58	375	1,356	4,146	12,000	23,325
wmnern33_i	88,065	2,786	21	60	382	1,379	3,911	9,670	15,834
nmwern33	1,271,797	3,294	29	90	495	1,461	3,981	11,170	23,519
nmwern33_c	661,720	3,499	29	95	555	1,710	4,517	11,424	22,154
nmwern33_i	89,647	2,525	23	65	378	1,258	3,457	8,745	14,679
nmnern33	597,735	1,631	12	30	120	378	1,200	6,243	14,888
nmnern33_c	308,603	2,049	13	32	153	554	2,011	8,129	16,625
nmnern33_i	48,337	2,761	30	97	567	1,725	3,993	8,726	12,821

Table 3.22: Kansas Earnings Percentiles

Variable	N	Mean	1st Pctl	5th Ptcl	25th Pctl	50th Pctl	75th Pctl	95th Pctl	99th Pctl
ern32	2,473,180	4,967	27	119	1,148	3,639	6,654	12,916	24,601
ern32_c	1,233,094	5,036	27	94	1,069	3,572	6,659	13,553	25,123
ern32_i	399,864	4,522	25	91	803	2,987	6,007	12,158	24,897
wmwern32	1,724,976	6,203	128	576	2,700	4,931	7,754	14,026	27,489
wmwern32_c	859,007	6,351	86	511	2,656	4,924	7,840	14,899	28,308
wmwern32_i	267,600	5,877	95	431	2,271	4,466	7,248	13,510	29,329
wmnern32	278,691	2,463	15	46	307	1,007	2,799	8,549	18,000
wmnern32_c	141,622	2,306	15	42	236	875	2,567	8,010	18,575
wmnern32_i	43,963	1,621	14	34	182	575	1,677	6,055	12,938
nmwern32	274,631	2,213	25	80	411	1,071	2,602	7,402	15,002
nmwern32_c	134,681	2,010	24	66	358	960	2,323	6,891	13,633
nmwern32_i	53,261	1,898	24	65	310	831	2,093	6,636	14,284
nmnern32	194,882	1,489	9	24	105	348	1,100	5,663	13,598
nmnern32_c	97,784	1,611	10	25	104	368	1,238	6,195	14,989
nmnern32_i	35,040	1,805	12	27	124	412	1,386	6,895	16,851

Table 3.23: Missouri Earnings Percentiles

Variable	N	Mean	1st Pctl	5th Ptcl	25th Pctl	50th Pctl	75th Pctl	95th Pctl	99th Pctl
ern40	5,612,244	5,578	30	120	1,222	3,790	7,119	14,679	31,100
ern40_c	2,842,196	5,454	27	108	1,113	3,679	7,043	14,445	30,131
ern40_i	978,614	4,537	23	76	675	2,725	5,959	12,799	25,978
wmwern40	3,891,799	7,099	159	720	2,986	5,256	8,485	16,284	36,192
wmwern40_c	1,955,692	7,053	148	701	2,986	5,253	8,500	16,079	35,102
wmwern40_i	581,959	6,439	108	521	2,599	4,823	7,819	14,789	31,339
wmnern40	671,744	2,689	17	51	321	1,049	2,845	9,085	20,643
wmnern40_c	347,757	2,194	15	41	247	798	2,188	7,609	17,721
wmnern40_i	161,349	1,700	13	35	196	632	1,758	6,148	13,469
nmwern40	588,668	2,082	30	87	432	1,081	2,398	6,748	13,643
nmwern40_c	309,560	2,018	23	76	388	992	2,251	6,547	13,960
nmwern40_i	129,503	2,003	27	70	347	911	2,111	6,435	14,820
nmnern40	460,033	1,400	10	26	102	309	901	4,384	13,199
nmnern40_c	229,187	1,398	10	26	103	310	912	4,651	14,361
nmnern40_i	105,803	1,502	12	28	113	339	1,015	5,208	16,115

Table 3.24: Pennsylvania Earnings Percentiles

Variable	**N**	**Mean**	**1st Pctl**	**5th Ptcl**	**25th Pctl**	**50th Pctl**	**75th Pctl**	**95th Pctl**	**99th Pctl**
ern48	11,910,032	6,444	40	178	1,591	4,647	8,505	16,965	36,693
ern48_c	5,961,281	6,248	35	148	1,372	4,392	8,358	16,727	35,698
ern48_i	5,901,874	6,246	35	148	1,370	4,389	8,357	16,724	35,692
wmwern48	8,600,650	7,803	176	756	3,243	6,050	9,696	18,350	40,887
wmwern48_c	4,277,963	7,716	154	702	3,114	5,964	9,692	18,217	40,229
wmwern48_i	4,235,182	7,715	154	701	3,113	5,963	9,693	18,215	40,216
wmnern48	1,355,701	3,469	21	64	424	1,440	4,111	12,252	25,590
wmnern48_c	691,315	2,581	17	45	269	904	2,749	9,832	21,059
wmnern48_i	684,575	2,572	17	45	268	900	2,735	9,801	21,001
nmwern48	1,210,112	2,982	35	111	524	1,338	3,334	10,545	22,273
nmwern48_c	616,852	2,730	32	93	447	1,165	2,923	9,757	21,700
nmwern48_i	610,872	2,728	32	93	446	1,163	2,919	9,754	21,709
nmnern48	743,569	1,783	12	32	135	415	1,275	6,489	19,000
nmnern48_c	375,151	2,047	12	32	148	453	1,425	7,269	22,578
nmnern48_i	371,245	2,049	12	32	148	453	1,424	7,267	22,613

3.2 Hours Imputation

The number of hours spent at work is unfortunately not provided by the UI wage records. Instead, crosswalks between survey and administrative data provide hours worked information for individuals with UI records who appear in the 2000 Decennial Sample Census Edited File (SCEF). The goal is to specify a model for annual hours of work (at all jobs) conditioning on year, sex, race, foreign-born, number of jobs held, 6-quarter annual work pattern, and total labor earnings decile that occurs in the population. These total hours are then partitioned amongst all jobs, by percent of earnings.

For each combination of the conditioning variables, the predicted probabilities times the sample count of individuals with those characteristics constitutes the likelihood contribution to the posterior distribution. Using empirical Bayes methods with informative priors that are based on aggregated data, the Dirichlet prior for each group has shape parameters given by the 2000 SCEF estimate of the proportions of usual weekly hours for sex and race, and prior sample size, which is arbitrary.

3.2.1 Identification

We observe a set of data $\{H_i, Z_i, w_i, m_i\}_{i=1}^{N}$, where H_i is the sum of annual hours for individual i over all jobs j, $H_i = \sum_{j=1}^{J_i} H_{ij}$; Z_i is a set of covariates we presume are related to annual hours; the instrument w_i is person-level earnings stated in year 2000 dollars, $w_i = \sum_{j=1}^{J_i} w_{ij}$; and m_i equals one if the annual hours are observed and is zero otherwise. Job j annual hours for individual i, H_{ij}, is the actual outcome of interest, where $H_i = \sum_{j=1}^{J_i} H_{ij}$. To impute the missing outcomes, we first need to draw from the probability

$$\pi(H_i|Z_i, m_i = 0) = \Pr[H_i|Z_i, m_i = 0]$$

to assign annual hours to each person. Then, for each person, we distribute the sum of annual hours to each job held in a given year.

The distribution of annual hours is never observed in the data, and so we must begin with identifying assumptions. For the first stage imputation of annual hours of work, H_i, we identify $\pi(H_i|Z_i, m_i = 0)$ by assuming that the data are missing completely at random, or that

$$\pi(H_i|Z_i, m_i = 0) = \pi(H_i|Z_i, m_i = 1).$$

Knowledge of annual hours depends upon whether an individual has a record of hours worked on the 2000 Decennial SCEF. Arguably, this means that the observability of the outcome is independent of the outcome, whether missing or observed. Given this identifying assumption, annual hours can be imputed by drawing from the posterior predictive distribution of annual hours in the observed data, conditional on all other information common to the two files.

In the second stage of the imputation- the assignment of hours to jobs- the outcome H_{ij} is dependant upon the jobs held. Again, we want to model $\pi(H_{ij}|Z_i, m_i = 0)$, but in this case, $m_i = 0$ for every observation in the sample since no job-specific hours information is provided. To identify the distribution, we assume that

$$\pi(H_{ij}|Z_i, m_i = 0) = \pi(w_{ij}|Z_i),$$

where w_{ij} is the wage and salary earnings of the job to which annual hours needs to be assigned. Earnings, w_{ij}, is observed for every worker and for every job, so this assumption completely identifies the distribution of work hours across jobs.

3.2.2 An Empirical Bayes Procedure

Now consider the general problem of learning $\pi(H_i|Z_i)$ given a set of data

$$\{H_i, Z_i\}_{i=1}^{N}.$$

It will be convenient to think of the data as $\{H_i\}_{i=1}^{N_Z}$, where N_Z is the size of the subsample of observed data with $Q = 52 \times 99 = 5,148$ covariate cells defined by Z. The outcome of interest is $H_i \in H$, where $H = \{H_1, ..., H_Q\}$ is a discrete support. Because of this, $\pi(H_i|Z_i)$ may be parameterized without loss of generality as a multinomial distribution with parameter $\theta = (\theta_1, ..., \theta_Q)$.

The posterior distribution of θ follows Bayes' rule:

$$\pi(\theta|H, Z) = \frac{\pi(H|\theta, Z)\pi(\theta|Z, u)}{\int_\theta \pi(H|\theta, Z)\pi(\theta|Z, u)d\theta}.$$

Assuming that the observations are independent, the likelihood of the data is

$$\begin{aligned} \pi(H|\theta, Z) &= \Pi_{i=1}^{N_Z}\Pi_{k=1}^{Q}\theta_k^{\mathbf{1}(H_i=H_k)} \\ &= \Pi_{k=1}^{Q}\theta^{N_{Z_k}} \end{aligned}$$

where $N_{Z_k} = \sum_{i=1}^{N_Z} 1(H_i = H_k)$. That is, N_{Z_k} is the count of observations with covariates Z and outcome $H_i = H_k$.

The prior on θ is Dirichlet with parameter u

$$\pi(\theta|Z, u) = \frac{1}{M(u)}\Pi_{k=1}^{Q}\theta_k^{u_k-1},$$

so we have

$$\pi(H|\theta, Z)\pi(\theta|Z, u) = \frac{1}{M(u)}\Pi_{k=1}^{Q}\theta_k^{N_{Z_k}+u_k-1}.$$

Note that $\int_p \pi(H|p,Z)\pi(p|Z,u)dp$ must satisfy

$$\begin{aligned}\int_\theta \pi(H|\theta,Z)\pi(\theta|Z,u)d\theta &= \int_\theta \frac{1}{M(u)}\Pi_{k=1}^{Q}\theta_k^{N_{Z_k}+u_k-1}d\theta \\ &= \frac{1}{M(u)}\int_\theta \Pi_{k=1}^{Q}\theta_k^{N_{Z_k}+u_k-1}d\theta \\ &= \frac{M(N_Z+u)}{M(u)}.\end{aligned}$$

This gives us

$$\pi(\theta|Z,H) = \frac{1}{M(N_Z+u)}\Pi_{k=1}^{Q}\theta_k^{N_{Z_k}+u_k-1}.$$

That is, the posterior distribution of the multinomial parameter θ is Dirichlet with parameter $v = N_Z + u$ where $N_Z = (N_{Z_1}, ..., N_{Z_Q})$.

3.2.3 Data and Imputation

The base sample for the hours imputation are the individuals who comprise the 2000 Decennial Sample Census Edited File (SCEF). The 2000 SCEF inquires about usual weekly hours and weeks worked in the previous calendar year. From these variables, it is possible to construct annual hours in 1999 for respondents who worked during that time frame. Annual hours in the SCEF are recorded as the number of hours worked per week times the number of weeks worked in 1999. Hours per week are restricted to be an integer between 1 and 99 so the number of possible outcomes is $99 \times 52 = 5,148$. Demographic information is acquired from the ICF to be consistent with the human capital estimation. Date of birth is converted into 1999 age, which is age as of December 31, 1998. Sex becomes an indicator for males, and race transforms into a white variable. Foreign born status is merged in through the Person Characteristics File, a Census extract of the Social Security Administration's Numident.

These records are then linked to the1999 EHF. Only individuals who are 14-85 and who have positive annual hours in the SCEF and positive earnings in the 1999 EHF are retained in the sample of the estimation file. Variables for the number of jobs held, a 6-quarter work pattern window, and cumulative annual earnings are generated at the person level. A second file of person-level information for all individuals who ever worked in 1999 who are 14-85 is used to generate deciles of the annual earnings distribution. On the pooled linked 1999 EHF and SCEF data file, a decile categorical variable is generated, which completes the list of conditioning variables.

There are 14,400 different combinations of the conditioning variables. Hence, there are 74,131,200 possible covariate annual hours cells. The conditioning variables, Z, in our annual hours imputation included the following for each year, 1990-2003:

- male: an indicator for sex equals male
- white: an indicator for race equals white
- born_us: an indicator for whether a worker was born in the United States
- nempl_cat: number of jobs held in UI data in that year, maximum value is 3
- sixqwindow: the person-level 6-quarter employment history covering all jobs during the four quarters of the current year and the quarters before and after this year
- decile: the worker's decile in the 1999 distribution of wage and salary income stated in year 2000 dollars.

Likelihood

The likelihood of the observed data requires finding the frequency count in each of the 74,131,200 cells. The number of observations in the sample with covariates Z_k is N_{Z_k}.

Prior

An interpretation of the parameters of the Dirichlet prior is that they provide the shape of the prior distribution and the prior "sample size," which measures our confidence in this shape. The shape parameter, u, for the annual hours imputation is a linear combination of an empirical prior and an uninformative uniform prior. The empirical prior comes from the frequency proportions, a, of the following set of conditioning variables each year: white, male, and nempl_cat. There are 12 categories for the prior, and a total of 61,776 cells. This is sufficiently coarse that each cell has non-zero frequency. To further smooth the posterior distribution, the complete prior was Dirichlet with parameter

$$u = 0.99a + 0.01b,$$

where b is the discrete uniform distribution over the 5,148 possible hours outcomes. Thus, the prior "sample size" is 1 (one person).

Imputation

Given covariates Z, the parameter of the Dirichlet posterior is $v = N_Z + u$. For each of the 14,400 combinations of the conditioning variables, Z, we draw once from the corresponding Dirichlet posterior to get θ. For a worker-year observation in the estimation sample with covariates Z, missing annual hours are imputed by making a single draw, H, from a multinomial distribution with parameter θ.

3.2.4 Hours per Job Imputation

Hours per job were estimated on the assumption that for each worker-year, there is an unknown distribution of hours across each of the worker's reported jobs for that year. Here, the number of outcomes is J_{it}, which is the total number of jobs held by worker i in year t. We assume that each hour is allocated to one of these jobs according to a multinomial distribution parametrized by θ_{it}.

Likelihood

We assume that the allocation of hours across jobs is identical to the allocation of dollars across jobs. So, we take w_{ijt} as the likelihood count for job j, where w_{ijt} are the annual earnings in job j of worker i in year t.

Prior

Because there is no further information about the allocation of hours, we assume a uniform prior, u_{it}.

Imputation

For every worker-year in the sample, to impute hours for each job, we draw once from the posterior Dirichlet with parameter $v_{it} = w_{it} + u_{it}$. This yields $v_{it} = (v_{i1t}, ..., v_{iJ_{it}t})$ as an estimate of the distribution of hours across jobs. The imputation of hours per job is completed by taking $H_{it}\hat{\theta}_{it}$.where H_{it} is the measure of annual hours (actual or imputed) for i in year t.

Our analysis involves processing data from several states in parallel. Since some workers appear in several states in the same year, we take measures to ensure that the annual hours and hours per job imputed for a worker appearing in multiple states are identical. We do this by assigning each worker–year observation a random draw from the uniform distribution that is the same in all states. This random draw is then used to draw annual hours, and to seed the random number generator used to impute hours for each job.

3.3 Experience Imputation

We have the ability to track accrued experience for individuals who remain in our sample of Unemployment Insurance wage records over time. However, determining the initial level of experience to assign to workers when they appear in the data is a less straightforward task. One manner of doing this is to define initial experience as potential experience based on age at first observation. A second, more accurate method involves taking draws from the posterior distribution of experience in administrative earnings data to assign this value. It is the latter style of imputation that we choose.

For persons in our UI data sample who were ever interviewed in the Survey of Income and Program Participation or Current Population Survey, we have Summary Earnings Records (SER) available from the Social Security Administration. The SER contain the annual earnings stream capped at the taxable maximum and annual quarters of covered work for each individual from 1951 until the present year, with estimates of quarters of covered work available for the period 1937-1951. By summing these quarters of work and dividing by four, we acquire an accurate measure of years of lifetime experience.[8] This file is merged with the Census Bu-

[8]The initial few years of experience for older workers is imputed based upon the year-to-year experience growth of young workers in the SER. This imputation is necessary because older workers experience profiles may be incomplete due to the initial date of available data in the SER.

reau's Person Characteristics File (PCF), a Census extract of the Social Security Administration's Numident, to acquire gender, birth location, date of birth, and years in the United States for each record.

Experience is classified within the following cells as of December 31, 2000: native born, sex, and age; foreign born, sex, and years in the US; and foreign born, sex, and age. This last category is necessary for our imputation of experience for those individuals who do not appear in the PCF and therefore have a missing birth location.[9] For them, gender and date of birth have already been imputed on our Individual Characteristics File for the Employment History File. A Kernel Density Estimate (KDE) smooths the values of experience for each gender, birth location, and time type (age or years in the US) cell. The categories are: native born males, native born females, foreign born males, foreign born females, males with missing birth location, and females with missing birth location. Categories that are too thin, as is the case with workers who are greatly advanced in age, are pooled.

The smoothed KDE estimate generates a density of experience, from which a cumulative density function (CDF) is derived. A uniform random number is assigned to those individuals requiring the experience imputation. This random number draw is used to make the initial experience assignment for when the individual first appears in the Unemployment Insurance wage records. The imputed value is based on the location of the random draw in the CDF distribution of experience. Any unreasonable draw that results in a value of initial experience that is greater than potential experience (calculated here as $age - 13$) is rejected and a new draw is made.

This imputation method allows people at varying points in their lives to have

[9] A missing birth location on the PCF is indicative that these people are not natives of the United States.

different accumulated experience. It incorporates labor force attachment behavior and cohort effects for each gender. Initial experience is assigned based on the primary year of observed work in the UI records. If experience differs systematically for those who move out of state (and out of our sample), then we will need to adjust for this in any models that use this imputation. The next section discusses the manner in which this type of selection can be corrected for by using a selection model.

3.4 Selection Models

We do not observe the complete work histories of individuals who appear in our sample states. This fact is elucidated by Table 3.1, which illustrates the entry year of each LEHD partner state into the data time series. Each period, some portion of a work history is not present for workers who have yet to move into a sample state, or who have left a sample state to seek employment elsewhere.

Selection models are estimated based on UI and decennial Census links to correct for the two types of selection bias in every year of our time series, 1990-2004, that result from this incomplete information. The first model addresses workers who exit a sample state to work in a state not in the LEHD data infrastructure (denoted by the IO, or "In-sample to Out-of-sample," specification). The second addresses employed individuals who move from an out-of-sample state into the LEHD data infrastructure (denoted by the OI, or "Out-of-sample to In-sample," specification):

$$e_{it}^{IO} = \begin{cases} 1, \text{ if work in a year } t \text{ sample state in period } p-1 \text{ and in a} \\ \text{year } t \text{ out-of-sample state in period } p \\ 0, \text{ if work in a year } t \text{ sample state in periods } p-1 \text{ and } p \end{cases}$$

$$e_{it}^{OI} = \begin{cases} 1, \text{ if work in a year } t \text{ out-of-sample state in period } p \text{ and in a} \\ \text{year } t \text{ sample state in period } p+1 \\ 0, \text{ if work in a year } t \text{ out-of-sample state in periods } p \text{ and } p+1 \end{cases},$$

where $t = 1990, 1991, ..., 2003$ are the years of available UI data. Period p refers to the year 2000 Census SCEF, $p-1$ refers to the 1999 UI data, and $p+1$ refers to the 2001 UI data.

The probit models take the form

$$e_{it}^{*} = X_{it}'\beta_t + u_{it},$$

where the vector of covariates consist of demographic and household characteristics described in the data section below and $u_{it} \backsim N(0,1)$. The base set of individuals for the estimation of each model is those who are in sample. In other words, those who work in a year t sample state in $p-1$ for the e_{it}^{IO} specification, and those who work in a year t sample state in $p+1$ for the e_{it}^{OI} specification form the frame for the probit. From the probit equation, estimated values of β_t are obtained, which are used to construct values of the predicted probabilities, $X_{it}'\hat{\beta}_t$, for all people with complete HCEF records. Inverse Mills ratios are calculated as

$$\hat{\lambda}_{it}(X_{it}'\hat{\beta}_t) = \begin{cases} \phi(X_{it}'\hat{\beta}_t)/[1-\Phi(X_{it}'\hat{\beta}_t)], \text{ if } e_{it}^{*} > 0 \\ \phi(X_{it}'\hat{\beta}_t)/\Phi(X_{it}'\hat{\beta}_t), \text{ otherwise} \end{cases}$$

and are included in the estimation of the human capital model to correct for selection bias.

3.4.1 Data

The primary task involves matching all workers who ever appear in the UI wage records to the Hundred Percent Census Edited File (HCEF, or Short Form) and

Sample Census Edited File (SCEF, or Long Form) from the 2000 decennial Census. All who appear in these Census files respond about their relationship to the head of household, so it is possible to generate variables for whether the household contains a married couple,[10] if it is a multiple-family household,[11] the number of people who live in the household, the number who are less than 18 years old, and the number who are older than 65. Hispanic ethnicity and home ownership[12] are also on the HCEF and are included as controls in this imputation model.

The Individual Characteristics File (ICF) provides basic demographic information regarding date of birth, gender, and race. Indicators for males and caucasians are constructed, as is a missing race variable. The following age categories are used: 16-20, 21-30, 31-40, 41-50, 51-60, and 61 years or more. Age is static over

[10]The following formulae identify whether a married couple exists in the household: if father/mother ge 2 or husband/wife ge 1 or (brother/sister ge 1 and brother-in-law/sister-in-law ge 1) or ((natural-born son/daughter ge 1 or adopted son/daughter ge 1 or stepson/stepdaughter ge 1) and son-in-law/daughter-in-law ge 1) or parent-in-law ge 2 or (uncle ge 1 and aunt ge 1 and cousin ge 1) or (grandfather ge 1 and grandmother ge 1) then hh_married=1. The main difficulty involved in discerning these relationships involves determining whether the uncle and aunt are married or are siblings. To best determine marital status, we required that a cousin also be present in the household when both an aunt and uncle live in the household. We did not attempt to determine whether each individual is themselves married, since relationships are related through the head of household and selecting, an an example, which brother is married to which sister-in-law when multiple individuals are present would be impossible.

[11]Multiple subfamilies exist when either (1) the household head is married and also present in the household is at least one of: father/mother, parent-in-law, son-in-law/daughter-in-law, brother-in-law/sister-in-law, nephew/niece, grandparent, uncle/aunt, cousin; or (2) the household head is not married and also present in the household is at least one of: grandchild, parent-in-law, son-in-law/daughter-in-law, brother-in-law/sister-in-law, nephew/niece, grandparent, uncle/aunt, cousin.

[12]Home ownership is defined by an affirmative answer to either the HCEF question, “Is this house, apartment, or mobile home owned by you or someone in this household with a mortgage or loan?” or, “Is this house, apartment, or mobile home owned by you or someone in this household free and clear (without a mortgage or loan)?”

the course of the year and is the age of the individual on December 31st of the previous year.

Additional variables are acquired from the Person Characteristics File (PCF) in order to control for country of birth and date of entry into the United States. The region of birth variable collapses the 367 country codes to the top 23 source countries (employment) and the associated geographic regions (36 categories total, including a missing location category).[13] This reduces the dimensionality of the problem for the Heckit imputation process. An indicator variable denotes those individuals who do not match to the PCF, which gives information about when variables are imputed on the ICF. All SCEF records match to the PCF, but this will be used in the SRMI imputation of $X'_{it}\hat{\beta}_t$ values for the 26.7% of individuals in the ICF who do not have decennial Census records. Years in the United States are binned into these categories: less than 5 years, 5-9, 10-19, and more than 20. Date of entry is used to generate an Immigration and Reform Control Act indicator for non-native individuals who entered the United States between 1987 and 1991, inclusive. Missing dates of entry are controlled for by an indicator.

The Employer History File is linked to the Employer Characteristics file so that a compatible sample of workers can be created in the UI and decennial Census files for the estimation of this model. UI coverage varies by state, but it is generally the case that excluded from the EHF are workers in the armed forces,

[13]These regions are: (1) the United States or territory, (1) Mexico, (2) Philippines, (3) India, (4) Germany, (5) Vietnam, (6) El Salvador, (7) Cuba, (8) Canada, (9) United Kingdom, (10) China, (11) South Korea, (12) Japan, (13) Taiwan, (14) Columbia, (15) Guatemala, (16) Poland, (17) Jamaica, (18) USSR, (19) Haiti, (20) Dominican Republic, (21) Iran, (22) Italy, (23) Peru, (24) Former Socialist Europe, (25) Western Europe, (26) Former Soviet Union, (27) Central Asia, (28) South East Asia, (29) Middle East and North Africa, (30) Caribbean, (31) Central America, (32) South America, (33) Africa, (34) Oceania, and (35) not specified or missing.

public administration, agriculture, forestry, fisheries, self-employed not incorporated, and the public sector.[14] To make a consistent sample of individuals for the Heckit estimation, we choose to retain UI workers at establishments with private ownership codes and in SIC divisions outside of public administration. To match the scope of the UI wage records, the SCEF 2000 sample is restricted to employed individuals[15] whose place of work is inside the United States who are in the class of workers who are private for profit, private not-for-profit, or self-employed in incorporated businesses and who do not work in agriculture, forestry, or fisheries.[16] Only those who are 16-75 on December 31 of the year prior to the year of estimation are retained for the Heckit, which essentially means that from December 31, 1998 through December 31, 2000 the workers must fall into that age range. Group quarters individuals are not used in the probit estimations.

3.4.2 Details of Selection Estimation

In-sample to Out-of-sample

Using the matched ICF-SCEF sample as a universe with the aforementioned restrictions imposed, the 1999 UI records from states in year t serve as a base for this analysis with movement across state borders observed through comparisons with the place of work variable on the 2000 SCEF. We aim to estimate movement from working in 1999 an in-sample UI state in year t to working in the 2000 SCEF in an out-of-sample state (defined as the complement to the set of UI states in

[14]The SEIN ownership code should be “5” to indicate all private establishments, and the corresponding SIC division cannot be “J,” which is public administration.

[15]Those who are employed, at work, or employed, with a job but not at work.

[16]The following decennial Census industries are excluded: 017, 018, 018, 027, 028, and 029.

year t). Even though the frames for this analysis do not shift, the set of states considered in-sample do vary by year. Movements from employment within an in-sample state to employment in an out-of-sample state in year t are captured by the probit indicator variable, e_{it}^{IO}. The SCEF person weight is used in the model.

Out-of-sample to In-sample

Again using the matched ICF-SCEF sample as a universe with the aforementioned restrictions imposed, for this estimation, the 2001 UI records from states in year t serve as a base for this analysis with movement across state borders observed through comparisons with the state of work variable acquired from the 2000 SCEF data. We aim to estimate movement from working in 2000 an out-of-sample UI state in year t to working in the 2001 UI in an in-sample state (defined as the complement to the set of UI states in year t). Even though the frames for this analysis do not shift, the set of states considered in-sample do vary by year. Movements from employment within an out-of-sample state to employment in an in-sample state in year t are captured by the probit indicator variable, e_{it}^{OI}. The SCEF person weight is used in the model.

3.4.3 Imputing Missing Data

The Sequential Regression Multiple Imputation (SRMI) programs created by Woodcock and Benedetto (2006) are used to impute $X_{it}'\hat{\beta}_t$ for the 26.7% of the sample with incomplete information because they are present in the Unemployment Insurance wage records but have no decennial Census link.[17] Using a 1% sample of

[17] These missing data mainly result from individuals who were either not residing in the country or were deceased by 2000 and did not partake in the Census, but who worked during other years in our time series in the United States.

the complete data and all missing records, a two-sided Kernel Density Estimator (KDE) transform is used in a continuous model to impute estimates of $X'_{it}\hat{\beta}_t$ for those who are in the ICF and not in the HCEF. This is done within specified by-groups. These by-groups (By) and their covariates (X) for the imputation are as follows:

Groups:	G1	G1	G2	G2	G3	G3	G4	G4
Type:	By	X	By	X	By	X	By	X
male	1	0	1	0	1	0	1	0
white	1	0	1	0	1	0	1	0
agecat	1	0	1	0	1	0	0	1
born_us	1	0	1	0	0	1	0	1
born_foreign	1	0	0	1	0	1	0	1
missing_race	0	1	0	1	0	1	0	1
no_pcf	0	1	0	1	0	1	0	1
irca	0	1	0	1	0	1	0	1
years_us	0	1	0	1	0	1	0	1
years_us_missing	0	1	0	1	0	1	0	1

Definitions for these variables follow below:

$male$	- 1 if male, 0 if female
$white$	- 1 if white, 0 otherwise
$agecat$	- categorical age variable
$born\_us$	- 1 if born in the U.S., 0 otherwise
$born\_foreign$	- 1 if born outside the U.S., 0 otherwise
$missing\_race$	- 1 if race variable is missing, 0 otherwise
no_pcf	- 1 if no PCF record exists, 0 otherwise
$irca$	- 1 if non-native and entered U.S. 1987-1991, 0 otherwise
$years\_us$	- cumulative years spent in the U.S.
$years\_us\_missing$	- 1 if years in the U.S. are missing, 0 otherwise

All categorical covariates, such as $agecat$, $born\_foreign$, and $years\_us$, become indicator variables during the imputation. An Immigration and Reform Control Act indicator, $irca$, for non-native individuals who entered the United States between 1987 and 1991, inclusive, is among the covariates. Missing dates of entry and missing PCF links are controlled for by the indicators $years\_us\_missing$ and no_pcf, respectively. Cells with fewer than 1,000 records are passed into the next grouping.

3.5 National Weights- Industry and Demographic Control Totals

The temporal fluctuation of the set of states in our sample requires us to create annual weights that are associated with person and job characteristics. These weights permit our sample counts to match the corresponding totals of workers and establishments at the national level in each year. In this manner, they enable our results for the subset of states for which we have data to be interpreted for the entire United States. These weights are generated by raking LEHD data with equivalent cells to control totals based on Census Bureau population estimates and Bureau of Labor Statistics Current Establishment Survey estimates. These weights have the capability of being generated for any combination of states in our data sample. Described below are the three data sources used, followed by a description of the creation of the weights.

3.5.1 Industry Data (1990-2002)

Industry data are from the Current Employment Statistics (CES) program. The CES figure is defined as average monthly job counts of employees in nonfarm business payrolls over the year. The data are year by SIC division margins, with the yearly data referencing the second quarter.

3.5.2 Demographic Data (1990-2002)

The Annual Social and Economic Supplement to the Current Population Survey (1990-2002) provides us with the demographic data. The universe has been restricted to match the private nonfarm business sector reflected in the industry data provided by the CES. Any person age 14 or older who last year reported positive wages, weeks worked, and hours per week is included except for government workers, those who have never worked, private household workers, members of the armed forces, and agricultural employees.[18] The data are constructed as year by

[18]Those typically not covered by Unemployment Insurance wage records (varies slightly by state: this is IL) are the federal civilian government, U. S. Postal Service, military, self-employed, insurance/real estate agents working solely on commission, railroad, judiciary, small agricultural businesses, elected state and local government

gender by age group by education group margins. Population totals in this survey (used to calculate the United States weights) are based on official Census Bureau population estimates.

The demographic data have been scaled down to the level of the industry data so that the annual totals agree. Scaling down the CPS data proportionately for all does not greatly affect the quality of the labor figures.

3.5.3 LEHD Sample Totals

A sample count, e_{dkt}, is constructed from Unemployment Insurance data on all states used to estimate the human capital model based on the SIC divisions that exist in both the CES industry and ES-202 data sets.

Here, k indexes sex by age group by education group, d indexes SIC division, and t indexes year. Employment is defined as the second quarter average of total beginning and ending employment ((B+E)/2) in order to be consistent with the definition of employment in the industry data. These data are stratified into year by SIC division by sex by age group by education group, with the yearly data referencing the second quarter.

3.5.4 Final Weights

Using the consistent control totals, iterative proportional fitting (IPF) on the marginal demographic and industry data is implemented by year to obtain a control weight, f_{dkt}, for each year, t (1990-2002), demographic category, k, and industry sector, d, that is fitted to the known distribution of an identical sample of UI and

officials, National and Air National Guard, and underground economy. See also http://stats.bls.gov/opub/hom/homch5_b.htm.

ES-202 data. The final weight used is given by

$$weight_{dkt} = \frac{f_{dkt}}{e_{dkt}},$$

which is the ratio of the control total to the equivalent sample size total for each set of characteristics. Here, k indexes sex by age group by education group and i indexes SIC division. The number of categories for each variable of cross-classification are as follows: 12 years (1990-2002), 8 SIC divisions, 2 sexes, 8 age groups, and 6 education groups. The SIC divisions to be included are: mining, construction; manufacturing; transportation, communication, and public utilities; wholesale trade; retail trade; finance, insurance, and real estate; and services. Age groups are defined as CPS age groups: 14-18, 19-21, 22-24, 25-34, 35-44, 45-54, 55-64, and 65 or more years.[19] Education groups are defined as: 0-8, 9-11, 12, 13-15, 16, and 17 or more years of schooling.

3.6 Human Capital Input File Summary Statistics

For the 30 states in this run, approximately 160 million persons ever held a job between 1990 and 2003. The top three job holders have 43,911; 10,120; and 6,386 jobs during that time. Only about 15,000 individuals have more than emax=88 jobs between 1990 and 2003, which is less than one hundredth of one percent of the sample. Roughly 1.675 billion year-person-establishment records are input, with 2.3 billion year-person-establishment records processed. The difference is due to individuals who work in more than one state: 81% of the sample has worked in only one state; 15% of the sample has worked in two states; 3% of the sample has worked in three states; the remaining individuals worked in four or

[19]The maximum allowable age is 85.

more states, although few have worked in more than ten. In the final estimation with all restrictions imposed, 1,005,326 observations; 417,946,932 cells; 154,106,229 persons; and 9,090,173 firms are present.

3.7 Concluding Remarks

Following the completion of the data preparation of the infrastructure files, the estimation of the Heckit selection model, and the creation of national weights, the human capital estimates are generated. The model and methodology for the estimation is described in detail in the preceding chapter.

BIBLIOGRAPHY

Abowd, J. M., J. Haltiwanger, R. Jarmin, J. Lane, P. Lengermann, K. McCue, K. McKinney, and K. Sandusky (2005). The relation among human capital, productivity and market value: Building up from micro evidence. In C. Corrado, J. Haltiwanger, and D. Sichel (Eds.), *Building Up from Micro Evidence*, Chapter 5. Chicago: The University of Chicago Press.

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999, March). High wage workers and high wage firms. *Econometrica 67*(2), 251–334.

Abowd, J. M., P. A. Lengermann, and K. L. McKinney (2002, August). Measurement of human capital in the U. S. economy. LEHD Technical Paper TP-2002-09.

Baker, M., M. Stabile, and C. Deri (2004, Fall). What do self-reported, objective, measures of health measure? *The Journal of Human Resources 39*(4), 1067–1093.

Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education.* New York: Columbia University Press.

Blau, D. M. (1998, July). Labor force dynamics of older married couples. *The Journal of Labor Economics 9*(3), 595–629.

Bradley, C. J., H. Bednarke, and D. Neumark (2001, February). Breast cancer survival, work, and earnings. NBER Working Paper 8134.

Butler, J. S., R. V. Burkhauser, J. M. Mitchell, and T. P. Pincus (1987, November). Measurement error in self-reported health variables. *The Review of Economics and Statistics 69*(4), 644–650.

Charles, K. K. (1999). Sickness in the family: Health shocks and spousal labor supply. Working Paper 00-011.

Chirikos, T. and G. Nestel (1985, February). Further evidence on the economic effects of poor health. *The Review of Economics and Statistics 67*(1), 61–69.

Coile, C. C. (2004, September). Health shocks and couples' labor supply decisions. NBER Working Paper 10810.

Currie, J. and B. C. Madrian (1999). Health, health insurance and the labor market. *3*, 3309–3416.

Daly, M. C. and J. Bound (1995, July). Worker adaptation and employer accomodation following the onset of a health impairment. NBER Working Paper 5169.

Dean, E. R. and M. J. Harper (1998, March). The BLS productivity measurement program. In *Conference on Research in Income and Weath: New Directions in Productivity Research*. Discussion paper.

Dean, E. R., M. J. Harper, and P. F. Otto (1995, October). Improvements to the quarterly productivity measures. *Monthly Labor Review*, 27–32.

Fairlie, R. W. and L. G. Kletzer (1998, October). Jobs lost, jobs regained: An analysis of black/white differences in job displacement in the 1980s. *Industrial Relations 37*(4), 460–475.

Fallick, B. C. (1996, October). A review of the recent empirical literature on displaced workers. *Industrial and Labor Relations Review 50*(1), 5–16.

Greene, W. H. (1997). *Econometric Analysis*. New Jersey: Prentice Hall.

Haurin, D. R. (1989, February). Women's labor market reactions to family disruptions. *The Review of Economics and Statistics 71*(1), 54–61.

Heckman, J. J. (1979, January). Sample selection bias as a specification error. *Econometrica 47*(1), 153–161.

Ho, M. S. and D. W. Jorgenson (1999, February). The quality of the u.s. work force, 1948-1995. Mimeo, Harvard University.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993). Earnings losses of displaced workers. *American Economic Review 83*(4), 685–709.

Jorgenson, D. W., F. M. Gollop, and B. M. Fraumeni (1987). *Productivity and U. S. Economic Growth*. Cambridge: Harvard University Press.

Kahn, M. (1998, October). Health and labor market performance: The case of diabetes. *Journal of Labor Economics 16*(4), 878–899.

Kletzer, L. G. (1998, Winter). Job displacement. *Journal of Economic Perspectives 12*(1), 115–136.

Kletzer, L. G. and R. W. Fairlie (2003, July). The long-term costs of job displacement for young adult workers. *Industrial and Labor Relations Review 56*(4), 682–698.

Lee, L.-F. (1982, February). Health and wage: A simultaneous equation model with multiple discrete indicators. *International Economic Review 23*(1), 199–221.

Lengermann, P. (2002, May). A comparison of LEHD human capital measures with traditional measures. Working Paper.

Mincer, J. (1974). *Schooling, Experience, and Earnings*. New York: Columbia University Press.

Ong, P. M. (1991). Race and post-displacement earnings among high-tech workers. *Industrial Relations 30*(3), 456–468.

Panis, C., R. Euller, C. Grant, M. Bradley, C. E. Peterson, R. Hirscher, and P. Steinberg (2000, June). *SSA Program Data User's Manual*. Report for the Social Security Administration.

Parsons, D. O. (1977, September). Health, family structure, and labor supply. *The American Economic Review 67*(4), 703–712.

Rubin, D. B. (1987). *Multiple Imputation for Nonresponse in Surveys*. New York: John Wiley & Sons, Inc.

Rubin, D. B. (1996, June). Multiple imputation after 18+ years. *Journal of the American Statistical Association 91*, 473–489.

Ruhm, C. J. (1991, March). Are workers permanently scarred by job displacements? *The American Economic Review 81*(1), 319–324.

Smith, J. P. (1999, Spring). Healthy bodies and thick wallets: The dual relation between health and economic status. *The Journal of Economic Perspectives 13*(2), 145–166.

Social Security Administration (2003). *Annual Statistical Supplement to the Social Security Bulletin*. Social Security Administration. SSA Publication No. 13-11700.

Social Security Advisory Board (1998). *How SSA's Disability Program Can Be Improved*. Social Security Advisory Board. Report No. 6.

Stephens, M. (2001, April). Worker displacement and the added worker effect. NBER Working Paper 8260.

Stevens, A. H. (1997, January). Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics 15*(1), 165–188.

Stinson, M. (2003, June). Estimating the relationship between employer-provided health insurance, worker mobility, and wages. LEHD Technical Paper TP-2002-23.

Thomas, D. (2001, May). Health, nutrition, and economic prosperity: A microeconomic perspective. Working Paper WG1:7.

U. S. Department of Labor and Bureau of Labor Statistics (1993, December). *Labor Composition and U. S. Productivity Growth, 1948-90*. U. S. Department of Labor and Bureau of Labor Statistics. Bulletin 2426.

Woodcock, S. D. and G. L. Benedetto (2006). Distribution-preserving disclosure limitation. Working Paper.