Essays in Labor, Health, and Environmental Economics

by

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To my family

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CHAPTER I

Introduction

This dissertation consists of one essay on labor demand and environmental regulation, and two essays on family health and labor supply.

In chapter II, I examine the local labor market impacts of an environmental regulation: protection of the northern spotted owl under the Endangered Species Act. I use geographic data on the location and size of critical habitat areas set aside from logging to protect the spotted owl in the Pacific Northwest and northern California to identify the proportion of the observed decline in timber employment and earnings in the 1990s that can be linked to owl protection. I find that approximately sixty percent of the 30,000 lost timber jobs in the region and a decline of 2 percent in earnings per worker can be attributed to protection of the spotted owl.

In chapter III, co-authored with Robert F. Schoeni and Robert J. Willis, we investigate how parents' health is associated with children's human capital accumulation, manifested in educational attainment. Human capital theory predicts that children in families with fewer resources achieve lower levels of educational attainment. Having unhealthy parents, independent of financial resources, may therefore lead to lower educational attainment for children. Using data from the Health and Retirement Study, we find evidence that children with unhealthy parents attain less education than similar children with healthy parents. Controlling for family assets and other background characteristics, daughters are significantly less likely to complete as many years of education as sons if their mother experiences a decline in health. This is particularly striking for younger children – for ages 12-15, daughters and sons are expected to achieve less education if their father has a health decline, but for daughters that probability is 1.5 times as large if the mother experiences the health decline. One possible explanation for the gender difference is caregiving for an ill parent. Overall, we empirically establish a negative association between changes in parents' health and children's educational attainment.

In chapter IV, co-authored with HwaJung Choi, we describe the long-term association of poor parental health on children's labor force outcomes in adulthood. We hypothesize that poor parental health reduces family resources and harms children's human capital accumulation. These two factors have competing effects on children's labor supply as adults: lower family income and increased medical expenses for ill parents increases the incentive to work, while the reduction in human capital leads to lower wages, reducing the incentive to work. To describe this long-term association empirically we use two representative, longitudinal studies with detailed information on parents' health and children's labor force status: the Panel Study of Income Dynamics and the Health and Retirement Study. We show evidence of a long term association of poor parental health and children's reduced labor force participation. Young adults, ages 18 to 29, whose parents reported being in poor health were less likely to be working ten years later, compared to similar young adults with healthier parents.

CHAPTER II

Environmental Regulation and Labor Demand: the Northern Spotted Owl

2.1 Introduction

The listing of the northern spotted owl as threatened under the Endangered Species Act is widely regarded as one of the most dramatic and controversial environmental regulations in the last 30 years, particularly regarding employment impacts and reserved land areas. The regulation drastically reduced timber harvests on federal forest lands in the Pacific Northwest, leading many to conclude that large declines in timber industry employment in the 1990s were driven primarily by owl protection. Regulation to protect the northern spotted owl, indeed, had potentially the largest localized labor market impact of any U.S. environmental regulation. However, while the literature has focused on estimating the impact of owl protection on the output market for lumber and wood products and an input market: timber harvest, few studies have focused on the link between owl protection and local labor markets.

This paper aims to determine what proportion of the observed declines in timber employment and earnings per worker in the Pacific Northwest and California in the 1990s can be explained by protecting the northern spotted owl. The spotted owl lives in old-growth forest, highly valued by the timber industry. Protecting the spotted owl was a controversial regulation, pitting environmentalists against the timber industry in the 1990s. The impact on local labor markets was projected to be a substantial decline over the following ten years, yet surprisingly few studies have focused on estimating that impact.

The debate over the impacts of protecting the northern spotted owl made its way from state and federal policy and industry spheres into the popular media. Time magazine (Gup (1990)) ran a cover story about the owl controversy in June, 1992, during the week when the spotted owl was listed as "threatened" under the Endangered Species Act. The title of the article: "Owl vs. Man". Time magazine stated, based on U.S. Fish and Wildlife's estimates, that the projected impact of cutting timber production by more than 33% on federal forestland in the region would be 30,000 lost timber jobs.

At the time surrounding the listing of the spotted owl, there were a large number of studies predicting the local economic effects of owl-protection. These predictive estimates of employment declines varied widely, explained by different economic assumptions and political points of view. Goodstein (1999) conducts a review of these estimates. For the direct employment effects of owl protection Goodstein finds that estimates ranged from 21,000 to 87,000 lost jobs in the timber industry, projected over the following decade.

Compared to the plethora of predictive studies, there are relatively few retrospective estimates of the actual employment impacts. The U.S. Forest Service recently produced a 10-year retrospective analysis of the Northwest Forest Plan[1] (Charnley et al. (2006)). They conclude that 11,400 timber industry jobs were lost from 1990 to

[1]The Northwest Forest Plan (NFP) was an agreement outlining a forest management plan for the region, brokered by the Clinton administration in early 1994 (Tuchmann et al. (1996)).

2000 due to owl protection.

This paper's contribution consists of using a more precise measure of local implementation of the regulation: critical habitat areas established under the Endangered Species Act. Spatial data on federal forests and critical habitat areas, where logging was restricted in order to protect the spotted owl, provide a more precise measure of local implementation of the regulation, relative to previous work. Additionally, because critical habitat areas vary in size across counties within the region, this allows for the estimation of the marginal impact on local labor markets of an increase in the size of critical habitat areas.

My identification strategy relies on creating treatment and comparison groups of counties in the region, based on the location of critical habitat areas. I compare these two groups to infer the impact of owl protection on local employment and earnings, both within the timber industry and across other sectors. In addition, by using detailed geographic data on the size of owl protected areas, I am able to estimate the marginal effect of an additional acre of protected area on employment and earnings. Possible spillover effects, where unemployed timber workers may have relocated to other local areas and other sectors, are also considered.

I estimate the overall impact on labor markets in the Pacific Northwest, by comparing changes in employment and earnings between timber-producing counties, both before and after the regulation protecting the spotted owl. Results indicate that timber employment declined by 26 percent, and timber earnings per worker may have declined by 2 percent, from 1990 to 2000. Based on observed levels of timber employment in the region, this implies a loss of 17,600 timber industry jobs due to owl protection. Estimates from a comparison across regions, rather than within the region, imply a loss of 7,700 timber industry jobs.

The next section provides background on the related literature. Section 2.3 discusses policy aspects of the northern spotted owl controversy in the Pacific Northwest, provides background on the timber industry, and describes critical habitat areas set aside to protect the spotted owl. Section 2.4 describes the data and outlines my estimation strategy for examining the local labor market impacts of regulation-driven declines in timber harvest. Section 2.5 focuses on local labor market impacts; employment and earnings effects, and discusses spillover effects. Section 2.6 describes the labor market impacts when compared to other regions, particularly the Canadian province of British Columbia, and Section 2.7 concludes.

2.2 Related Research

Previous work on estimating the employment impacts of protecting the northern spotted owl has taken varied approaches. The U.S. Forest Service report (Charnley et al. (2006)) uses a comparison of rural and urban counties inside the Northwest Forest Plan area, which is composed of the western portions of Washington, Oregon, and Northern California. They estimate a loss of 11,400 timber industry jobs using results from an IMPLAN model[2] with county-level Census data from 1990 and 2000.

Berck et al. (2003) focus on timber-dependent counties only in northern California. They estimate economic impacts of spotted owl regulation on local communities, specifically focusing on poverty indicators. In previous work, they present an overview of estimation techniques for employment impacts of environmental policy (Berck and Hoffmann (2002)). They present a brief critique of using multiplier models for estimating the impacts of a change in activity level in one industry. Such models necessarily assume a fixed, proportional change in all the inputs used by that indus-

[2]IMPLAN is an input-output multiplier model commonly used by government agencies to estimate regional policy impacts, and was originally developed by the U.S. Forest Service. More information is available at `http://www.implan.com`.

try, not allowing for substitution effects. Freudenburg et al. (1998) use a longer time series of timber employment data, back to the 1940s, to estimate the employment impact of spotted owl protection. They compare the most recent declines to those employment declines linked to pre-1990s forest management policy changes. Using state-level data for Oregon and Washington, they conclude that time series breaks prior to 1990, specifically the Wilderness Protection Act of 1964, played a larger role in employment declines than spotted owl regulation, and thus assign spotted owl protection a small role, from a historical perspective.

In terms of the spotted owl, no research has yet to estimate the marginal impacts of an additional acre of critical habitat. Lewis et al. (2002) estimate the marginal impact of public forest conservation on employment growth, through mobility, but do so for a different region of the U.S.: the Northern Forest Region (northern Minnesota to Maine). Similarly, I estimate the marginal effect of an additional acre of reserved habitat for the spotted owl.

Within the labor literature examining how local labor markets are impacted by demand shocks, it can generally be difficult to find exogenous variation in labor demand[3]. Bound and Holzer (2000) and Greenstone (2002) look at the U.S. economy as a whole, and construct instruments to identify shifts in demand. Bound and Holzer (2000) use shifts in the composition of major industries in different cities over time. Greenstone (2002) evaluates the impacts of the Clean Air Act amendments on U.S. manufacturing, using variation in compliance across counties, driven primarily by air patterns across counties rather than point-source pollution within the county. Greenstone estimates large employment losses for the most polluting manufacturing industries in the entire U.S. over the 1970s and 1980s, due to air pollution regulation.

[3]Other spotted owl studies do not directly focus on labor, but do estimate costs (Montgomery et al. (1994)) and/or welfare changes (Murray and Wear (1998), Wear and Murray (2004), and Daigneault and Sohngen (2008)).

Other studies rely on observed, reasonably exogenous changes that shift labor demand in certain regions. Black et al. (2005) study the impact of the U.S. coal boom and bust periods on local labor markets in Appalachia in the 1970s and 1980s. Treatment counties are defined as those with large amounts of coal reserves. Comparing treatment and comparison counties, they find significant changes in overall mining employment growth and earnings per worker for both the boom and bust periods. They also find significant evidence for spillover effects into employment in other sectors, primarily production of locally-consumed goods such as construction and services. Berman and Bui (2001) examine the impacts of air pollution regulations on industrial employment in Southern California and find no significant employment effects. They also create treatment and comparison groups, over time, region, and industries, and additionally compare their treated region to distant states in the U.S. that have a similar industrial mix, but are not subject to the stricter air pollution regulations in Southern California.

There is no consensus yet on the employment effects of environmental regulation. Most studies appear to find no measurable employment effects, but estimates can vary greatly by the focus and scope of the study. For example, in estimating the impacts of the Clean Air Act amendments on manufacturing employment, these studies find very different estimates whether they focus on the entire U.S. over decades Greenstone (2002)), or for a period of years within one region (Berman and Bui (2001)). In comparison to these approaches, I study a specific labor-intesive industry, perhaps providing the best chance of finding measurable employment impacts.

2.3 Preliminary Considerations

2.3.1 Policy Background

The northern spotted owl resides in old-growth forest areas of the Northwestern U.S., specifically western Washington and Oregon, and parts of northern California. Observers began to notice the relative scarcity of spotted owls in the 1970s. After several disagreements in the 1980s between environmental groups and the timber industry over federal forest management, a 1989 lawsuit by environmental groups led to an injunction against federal timber sales[4] in Washington and Oregon (Hoberg (2003)). With the injunction still in place, the northern spotted owl was listed as "threatened" under the Endangered Species Act on June 26, 1990 (Yaffee (1994)). Another legal injunction went into effect in 1991, restricting 10 million acres in 17 National Forests across Washington, Oregon, and California, thereby bringing federal logging in the region to a virtual standstill (Hoberg (2003)).

After the spotted owl was listed in 1990, it took a few more years of discussion and compromise to establish protected areas for the owl where timber harvesting would be no longer be allowed. Critical habitat areas were designated on federal forestland by the U.S. Fish and Wildlife Service on January 15, 1992. The critical habitat areas include 2.2 million acres in Washington, 3.3 million acres in Oregon, and 1.4 million acres in northern California (Fed (1990)). See Figure 2.1 for the distribution of the nearly 6.9 million acres of protected publicly-owned forestland. There is substantial variation in the size of critical habitat areas across counties and labor market regions in these three states. Critical habitat areas are only located on public forest land, but the majority of timber land in this region is publicly-owned. In the Pacific Northwest, half of the land area is forest land, and 80% of that is timber

[4] See Athey et al. (2008) for an in-depth explanation of federal timber sales and auctions.

land, i.e. capable of producing commerical amounts of lumber. Sixty percent of the forest land in the Pacific Northwest is publicly-owned, either federal, state or local (Smith et al. (2002)).

Responding to the escalating tensions between environmentalists and industry, the Clinton administration held a town-hall meeting on April 2, 1993, in Portland, Oregon. President Clinton, Vice-President Gore and other aids spent an entire day listening to concerned parties (Hoberg (2003)). A year later, in April 1994, the administration presented its policy solution: the Northwest Forest Plan. The plan became the cornerstone for conserving the northern spotted owl on 24.4 million acres of federal land in Oregon, Washington and California (Tuchmann et al. (1996)).

The impact on timber harvests in the late 1980s and early 1990s was dramatic. Between 1988 and 1996, timber harvests fell 87 percent on national forests and 38 percent overall in the region (Daniels (2005)). See Figure 2.2 for the declines in timber harvest from both public and private forests.

2.3.2 Industry Overview

The timber industry in Oregon, Washington, and California is a major supplier for the national market in lumber and wood products. In 1997, these three states alone produced twenty percent of GDP in the timber industry[5]. Timber-related jobs and income can be divided into two manufacturing sectors. The first sector includes industries that manufacture solid wood products. These industries are included in the Standard Industrial Classification under SIC 24. The second sector includes pulp and paper industries, and are included in SIC 26. The primary-processing industries in the solid-wood products sector are logging and logging contractors; sawmill, veneer and plywood mills; hardwood dimension and flooring mills; and special-product sawmills.

[5] author's calculations, 1997 state-level GDP from BEA for SIC 24: Logging and Wood Products.

The output market considered here, referred to as the timber industry, is the Lumber and Wood Products industry, classified by the Bureau of Economic Analysis during the 1980s and 1990s as SIC 24[6]. The industry includes establishments engaged in cutting timber and pulpwood; sawmills, planing mills, and panel board mills engaged in producing lumber and wood basic materials; and establishments engaged in manufacturing finished articles made entirely or mainly of wood or related materials. Prior empirical research characterizes Lumber and Wood Products as a national industry (Wear and Murray (2004)). However, factor markets are regarded as regional in scope, due to transaction costs. Here, inputs are capital, labor, and timber harvest (stumpage) (Daigneault and Sohngen (2008)).

Total observed loss in timber employment in the Northwest Forest Plan area, from 1990 to 2000, was 30,000 jobs (Charnley et al. (2006)). This includes the western parts of Oregon, Washington, and northern California, where forestry was vitally important to the local, rural economies. See Table 2.1 for a listing of counties in western Oregon, Washington, and northern California with measures of employment dependency on the timber industry. In some counties, timber employment in 1975[7] was greater than 5% of total employment. Some of those counties are: Clallam, Cowlitz, Grays Harbor, Klickitat, Lewis and Mason counties in Washington; Coos, Curry, Douglas, Klamath, Linn, and Polk counties in Oregon; and Del Norte County in California. In these forestry-dependent counties, timber industry earnings also made up a significant porportion of overall earnings, as listed in Table 2.1.

[6] `http://www.bea.gov/regional/definitions/nextpage.cfm?key=Lumber and wood products`

[7] The first year of available data for this study. See Section 2.4 for further explanation.

2.4 Data and Estimation Strategy

For information on timber industry employment and earnings in Oregon, Washington and California, I use annual county-level data for SIC 24: Lumber and Wood Products, available from the Bureau of Labor Statistics (BLS) for 1975 to 2000. The data is from the Quarterly Census of Employment and Wages; formerly ES-202, an establishment census, available on the BLS website. This dataset is a panel of establishments, and does not contain information on individual workers. In the establishment-level data, which is primarily collected for unemployment insurance purposes, a timber company may have their administrative office located in a different county from where all their logging takes place, and where the workers reside. Employment reports are for the county where the office is located. Consider a scenario where the company has logging operations in a county that has a some owl critical habitat area, but the administrative office is located in a different county. Then a measure of timber employment change due to owl protection using a county-level indicator for critical habitat areas will not capture the employment change as reported by the company's administrative office, and will be biased downwards. Employment will be reported as decreased, but only in the county *next* to the county with the owl protected area, where the administrative office is located. Therefore the indicator variable for owl protected areas may not produce any changes in estimated employment, using this identification strategy, if the administrative office is not in the same county as the protected area.

In addition to using county-level information to estimate the employment and earnings effects of owl-protection, I also perform a regional comparison. For regional employment and earnings data, I use U.S. Census data from the IPUMS, 1990 and 2000 five-percent surveys. These data allow observation of long-term changes, over

10 years. The most detailed level of geography in the census data are Public Use Microdata Areas (PUMAs), groupings of 100,000+ residents, for the Pacific Northwest and California. I use the regional level employment data to compare the timber industry declines with declines in British Columbia, a Canadian province located just north of the Pacific Northwest. Data for timber employment in British Columbia are available from the Canadian Labor Force Survey, collected by Statistics Canada.[8]

2.4.1 Critical Habitat Areas

I use spatial data on the critical habitat areas, established in January 1992, in order to create two new measures of local implementation of owl-protection regulation. The first measure is a county-level indicator for whether or not any critical habitat areas were established in 1992. Forty-eight counties out of a total of 133 counties in Oregon, Washington, and California have some areas of owl critical habitat, which prevented logging on public forest lands. Figure 2.3 shows these 48 treatment counties in the region[9], concentrated in western Oregon and Washington and northern California, and the 52 counties selected as a comparison group. The comparison counties all have some amount of publicly-owned timberland and some amount of timber industry employment, over the time period studied. See Figure 2.3 for a map of the Pacific Northwest and California showing the treatment and comparison counties. Data on National Forest and publicly-owned timberland areas in the Pacific Northwest is available through the U.S. Forest Service website[10].

Additionally, I estimate the marginal effect of increases in the area of owl protection, measured in acres[11]. I use spatial data on the locations of these owl critical

[8]Statistics Canada data series is available through the British Columbia government's website: `http://www.bcstats.gov.bc.ca/data/lss/labour.asp`.

[9]See Table 2.1 for a complete listing of these treatment counties

[10]U.S. Forest Service: `http://svinetfc4.fs.fed.us/clearinghouse/index.html`.

[11]Analyses using critical habitat areas as a fraction of public forest land in the county produce

habitat areas in the Pacific Northwest, from the Regional Ecosystem Office[12], which provides support for the Northwest Forest Plan. The establishment of owl critical habitat areas in 1992 covered 6.9 million acres of publicly-owed forest land, both National Forest and Bureau of Land Management areas, spread over Oregon, Washington, and northern California. For those counties with protected areas, the average area preserved for the spotted owl was 153,000 acres, and ranged from 7,000 acres to a maximum amount of 787,000 acres. Additionally, critical habitat areas could only be placed on publicly owned land, so I include county-level measures of both public and privately owned timberland areas in the empirical specifications. These county-level measures of timberland, both public and private, are from the pre-1990 time period, and are therefore not changing over my sample.

Previous, similar studies have not taken advantage of this level of geographic detail and have instead relied upon, e.g., an indicator for rural counties (Charnley et al. (2006)) as a proxy for relative concentrations of timber employment, or state-level measures (Freudenburg et al. (1998)). The two measures used in this paper more precisely measure the implementation of the regulation, at a local level. This preciseness in measuring the regulation's implementation allows the use of variation in the location and size of owl-protected areas to identify declines in timber employment and earnings linked to owl protection.

2.4.2 Estimation Strategy

If timber industry workers are relatively immobile and therefore counties are reasonable estimates of geography for local labor markets, then we expect to see a decline in timber employment and earnings in treatment counties, which have owl-protected

similar results.

[12]REO GIS data website: `http://www.reo.gov/gis/data/gisdata/`.

areas, relative to comparison counties. Considering the theory of labor market supply and demand, a decrease in labor demand while labor supply stays constant leads to a decrease in both employment and wages. Both timber and labor are inputs to the production of lumber and wood products. A decline in timber harvest due to regulations restricts the supply of timber as an input. This can lead to a decline in labor demand, if the output effect is larger than the substitution effect. Previous research has found that labor and timber are relative substitutes, but their elasticity of substitution is relatively small (Vincent et al. (1992)). It is reasonable to expect that for such a large negative shock in timber harvest, the output effect will dominate the substitution effect, and we expect a decline in labor demand. To test this empirically, I expect to find a decline in both employment and wages in the timber industry, in counties with owl-protected areas.

Table 2.2 reports the difference in annual growth in total employment and earnings per worker for treatment counties before and after the owl regulation. Treatment counties are those which had owl critical habitat areas established in 1992. The first row of Table 2.2 shows that the average level of timber industry employment, per county, fell markedly after 1990. From 1975-1989, before owl regulation, the average treatment county had 2,391 timber workers. That number fell, from 1990 to 2000, to an average of 1,846 timber workers. Timber employment shows negative growth for both time periods, however the decline was larger after owl-protection. The growth rate in timber earnings by county was positive prior to 1990, but fell to a zero growth rate afterwards. Finally, timber earnings per worker grew at a 5% rate from 1975-1989 in treatment counties, but fell from 1990 to 2000 to a 3% rate.

Table 2.3 presents before-and-after estimates for 1990, for treatment and comparison counties separately. The time period covered by the county-level data is 1975 to 2000, in annual averages. Pooled OLS coefficients are presented in Table 2.3, with the top half of the table showing, for treatment counties, estimates of the percentage decline in timber employment. The indicator for owl regulation, $post - 1990$, shows a range of declines, over eight statistically-significant specifications, from 28 to 32 percent declines in timber employment from 1991-2000 compared to 1975-1990. The simple difference in means: pre- and post-owl regulation is a decline of 32 percent, and is listed in column (1). Taking the average across counties, the difference between pre- and post-owl regulation employment is a decline of 27.6 percent, shown in column (2), and is statistically significant at the 1-percent level. The final specification with both county indicators and measures of the area of publicly-owned and privately-owned timberland in each county shows a statistically significant decline of 29.3 percent (column 8). Over the same time period and same specifications the decline in comparison counties ranges from -0.135, in column (4), to -0.009 in column (5); though none are precise enough to be statistically significant at even a ten percent level. Columns (4) and (6) - (8) include measures of the acreage of public and private timberland in the county, to control for observable characteristics that influenced the location of owl critical habitat areas and therefore classification here into treatment or comparison counties. Inclusion of timberland acreage brings the estimate for treatment counties to a decline of 29 percent, while for comparison counties, it is an imprecisely estimated 3 percent decrease in timber employment.

I use difference-in-differences estimation to assess the effect of owl habitat reserves on labor market outcomes. Variation in the location and size of owl-protected areas helps to identify the impact on timber industry employment and earnings in the Pacific Northwest and California. I compare timber employment and earnings in counties with owl-protected areas relative to counties without owl-protection, before and after 1990, when the regulation was implemented.

To estimate the decline in timber industry employment and earnings per worker that could be attributed to owl-protection, I use the following difference-in-differences (DD) specification:

$$\ln \mathrm{Y}_{ct} \quad = \quad \alpha + \delta(\text{post-1990})(\text{owl}) + \gamma_c + \lambda_t + \epsilon_{ct}, \tag{2.1}$$

where Y_{ct} is timber employment or earnings per worker for county c in year t. (owl) is an identifier for treatment counties. *post*-1990 takes the value of 1 for the years 1990 to 2000, and 0 for earlier years, back to 1975. The coefficient of interest is δ, which is the difference-in-differences estimate of the change in $ln(Y)$ due to treatment, and measures the semi-elasticity of labor demand and owl regulation. γ_c and λ_t are county and year indicators, included in a range of specifications. Additional county-level controls include measures of timberland acreage in each county, both privately and publicly-owned; an observable difference in the characteristics of counties that may have played a part in determining selection for critical habitat areas.

To estimate the marginal effect of an increase in the size of critical habitat areas, I utilize a specification similar to the above, but incorporating non-linearities in the size of owl-protected areas for ease of interpretation:

$$\begin{aligned} \ln \mathrm{Y}_{ct} \quad = \quad & \alpha + \delta_1(\text{post-1990})(\ln(\text{owl acres})) \\ & +\delta_2((\text{post-1990})(\ln(\text{owl acres}))^2 + \lambda_t \\ & +\beta_4 \ln(\text{owl acres}) + \beta_5(\ln(\text{owl acres}))^2 + \epsilon_{ct}, \end{aligned} \tag{2.2}$$

where *ln(owl acres)* identifies amounts of owl-protected habitat, and is differenced from the mean for ease of interpretation. δ_1 is directly interpreted as the marginal effect on timber employment of an increase in owl-protected habitat.

In addition to the restrictions on timber harvesting due to the spotted owl, a number of other factors were at play in terms of declining timber employment in the Pacific Northwest. Some of these confounding factors are: the recession in the early 1990s, the decline in demand for timber exports to Asian countries, restrictions on Canadian imports of timber and lumber, the shift towards more capital-intensive production, particularly in sawmills, and the shift in production away from the Pacific Northwest into the southern U.S.

The industry is very cyclical, and demand for lumber and wood products generally follows the business cycle (Wear and Murray (2004)). The recession in the early 1990s was driven, in part, by the housing market. The slowdown impacted demand for lumber and wood products. Production costs, perhaps driven by the restriction of timber supply related to owl protection, led to a shift in industry production from the Pacific Northwest to the U.S. Southeast (Abt (1987), Smith and Munn (1998), Wear and Murray (2004), Daigneault and Sohngen (2008)). At around this time, in the 1970s and 1980s, there was also an industry-wide shift towards more capital-intensive production (Abt (1987)).

Within the Pacific Northwest and California region, groupings of treatment and comparison counties are arguably subject to the same macroeconomic forces. Both should be equally affected by the cyclicality of housing starts and therefore demand changes for lumber and wood products, Canadian tariffs, and a general shift in federal timber policy towards more recreation and less timber production. If both groups have the same reactions, over time, to these factors but differ only in the implementation of spotted owl regulation, then the difference-in-differences estimator, δ, is appropriate and will capture the average effects on employment and earnings per worker. Specifically, the key identifying assumption is that timber employment trends would be the same in both the treatment and comparison county groups if there had been no owl-protection. If there were different trends over time, they would be confounded with any changes due to spotted owl regulation, and the difference-in-differences estimator would no longer capture the effect of the regulation alone.

In the next section, I present results that use variation in critical habitat areas within the Pacific Northwest and California to identify the declines in timber employment and earnings due to spotted owl-protection. The accuracy of this approach depends on the assumption that both the treatment and comparison counties in the region were equally impacted by the confounding factors listed above. To further explore the limits of this assumption, later in Section 2.6 I use a measure of regional employment, grouping together both treatment and comparison counties in the Pacific Northwest. I then compare changes in that measure to changes in timber employment in a nearby region: the Canadian province of British Columbia.

2.5 Local Labor Market Impacts

In this section, I investigate the local labor market impacts of the owl regulations. Protecting the spotted owl reduced timber harvests in federal forests with owl-protected areas, and therefore presumably reduced demand for timber workers as well.

All else equal, a decline in timber harvests should imply, through supply and demand theory, a decline in both employment and earnings in the labor market for timber workers. If workers are relatively immobile and counties are therefore reasonable estimates of geography for local labor markets, we can expect to see a decline in timber employment and earnings in treatment counties, relative to comparison counties.

2.5.1 Employment Effects

The top panel of Figure 2.4 shows timber employment, from 1975 to 2000, for both groups: treatment and comparison counties. Notice that timber employment in treatment counties, i.e. those with some critical habitat areas, is always greater than in comparison counties. Both series exhibit similar sensitivity to the business cycle, with declines in the recessions of the early 1980s and 1990s.

Table 2.4 presents difference-in-differences (DD) estimates for the natural log of timber employment using a range of sample sizes and specifications: pooled OLS for 1975-2000 combined with controls for amounts of timberland in each county and county and year indicators. Column (1), with four observations, shows the differences in the means between treatment and comparison counties, pre- and post-1990. The coefficient on $(post - 1990 * owl)$ is fairly robust across the specifications in Table 2.4 and estimated at -0.261 in the specification with the full set of indicators and timberland controls, in column (9). This indicates that timber employment in treatment counties declined by approximately 26 percent relative to comparison counties, from 1990 to 2000 as compared to 1975-1989. Average timber employment in a treatment county was 1,412 in the pre-owl-protection period (1975-1989), so this percent decline implies a loss of 368 timber jobs in the average county. To calculate the decline in total timber employment in treatment counties multiply the average number of jobs, 368, by the number of treatment counties, 48, implying an overall employment decline of approximately 17,600 timber jobs from 1990 to 2000.

The marginal effects of an additional acre of owl-protected area on timber employment, as specified in Section 2.4 can be estimated using acres of owl-protected areas, by county, for the treatment counties. Estimates of the marginal effect of an increase in the size of critical habitat areas on timber employment, measured as the natural log, are presented in Table 2.5. The first two rows report pooled OLS coefficients for a non-linear specification of $ln(owl\ acres)$ interacted with the policy dummy, $post - 1990$, presented as differences from the mean, for ease of interpretation. Instead of summing the linear coefficient with twice the quadratic term, the estimate reported in the top row, because of this transformation, is the marginal effect. I present estimates for eight specifications: pooled OLS, pooled OLS with controls for amounts of timberland in each county, and year and county indicators. The coefficient on $(post - 1990 * ln(owlacres))$, the marginal effect of an additional acre of owl-protected area, is robust across specifications, ranging from -0.11 to -0.06 and is estimated at -0.09 in the specification with timberland areas, and year and county indicators, in column (8). The interpretation of the marginal effect is a 0.09 percent decrease in timber employment for a one percent increase in $owl\ acres$. The average amount of owl-protected area, by county, in the group of treatment counties, is 153,000 acres. The average county with owl-protected area has a negative association between increased owl-protected areas, in terms of size within the county, and timber employment.

2.5.2 Earnings Effects

Table 2.6 presents the same approach and methodology as in Table 2.4, estimating equation 2.1, but for a different outcome variable: earnings per worker, in the timber industry. The coefficient of interest is consistently, but imprecisely, estimated as a decline of about 2 percent, ranging only from -1.3 to -3.7 percent across nine specifications. This implies a decline of 2 percent in timber industry earnings per worker, from 1990 to 2000. In the BLS data, the information available is the number of workers by industry and county, reported monthly, and the total compensation paid during the quarter. In this study, I use annual averages of both number of workers and total compensation, i.e. earnings. Because of data limitations, total compensation cannot be decomposed into hours and wages.

2.5.3 Spillover Effects

One serious concern with this research design and this particular policy, is that the regulation to protect the spotted owl may have also negatively impacted industries besides the timber industry and impacted other nearby counties that did not have critical habitat areas. We can classify these indirect effects of the regulation as either sectoral spillovers or geographic spillovers. Sectoral spillovers would consist of unemployed timber workers who remain in their county but find new work in a non-timber industry. Geographic spillovers would involve newly unemployed timber workers moving to nearby counties that don't have owl-protected areas in order to find work in the timber industry. If such mobility was occurring, then the estimates from the previous section would be biased, because the group of comparison counties was also indirectly "treated" by the owl regulation.

For illustrative purposes, first assume that there are no sectoral spillover effects. If so, changes in employment in non-timber industries in both treatment and comparison counties would be a good counterfactual for changes in timber employment, in terms of owl-protection. That is, if the spotted owl hadn't been protected and critical habitat areas weren't established, we would expect timber employment and earnings growth in the region to behave similarly to that of non-timber employment and earnings. In this setting, the difference-in-differences estimator, described in equation 2.1, will capture the impact of the treatment without bias.

If there are no spillover effects, and the comparison counties are not impacted by the owl regulations and local labor markets are defined by county boundaries, then we should see no change in timber harvests, employment or earnings, in the comparison counties. This would be a straight-forward partial equilbrium story, where owl-regulation only impacts one market. However, there is a real possibility of spillover effects, particularly into other sectors in the region. Of concern are also geographic spillover effects, where the timber industry increased production outside of areas with owl-protection. If labor markets are linked across counties, we would expect earnings per worker to fall. And if unemployed timber workers look for work in comparison counties, we expect to see timber harvests increase relatively, as well as timber employment.

The next set of results uses comparisons between the timber industry and non-timber industry (i.e. total employment minus timber employment in each county) to draw comparisons of labor market impacts within the region. Table 2.7 presents estimates similar to those in Table 2.4, but for non-timber industries instead of the timber industry. Assuming there are no spillover effects between sectors, we would expect to see no significant difference in non-timber industry employment and earnings per worker before and after 1990. Coefficients in Table 2.7 are close to zero, with some slightly positive and mostly slightly negative, but none are statistically significant among the nine specifications. The final specification, in column (9) implies a 0.5 percent increase in non-timber employment in treatment counties, but this is not statistically different from zero.

The counterfactual experiment for non-timber earnings per worker, however, leads to significant declines in earnings per worker, for non-timber employees. In Table 2.8, the estimated relative decline of 5 percent is statistically significant and robust across all nine specifications. One explanation for this effect on earnings would be that if job loss among timber workers caused them to search for work in non-timber industries, this may have increased the labor supply in treatment counties for non-timber industries. If labor demand for non-timber employees is relatively inelastic then such a shift would result in a negligible effect on non-timber employment, but a decline in average earnings per timber worker.

Finally, Tables 2.9 and 2.10 present triple difference estimates (DDD) of labor market impacts on employment and earnings per worker using three sources of variation: over time, i.e. pre- and post-1990, between treatment and comparison counties, and comparing timber and non-timber industries. These DDD estimates use three types of comparison groupings to control for as much unobserved variation as possible, and if the treatment counties are well-specified, would leave only the difference due to treatment, in this case, owl protection. As before, with the difference-in-differences estimation, to identify the impact of owl protection alone, we assume that other differences between groups do not vary over time. In Table 2.9, the coefficient of interest, ($post$-1990 $*$ $timber$ $*$ owl $= 1$), the estimate for timber employment in treatment counties after 1990, is fairly robust across nine specifications, and in column (9) is estimated as a decline of 29.5 percent. Due to the decline in non-timber earnings in treatment counties relative to comparison counties, in Table 2.10 the DDD estimate for earnings per worker is 3.8 percent and positive, though not statically significant in any specification.

As workers leave their jobs in the timber industry, due to a decrease in timber harvest in the region, they can either stay in unemployment (not measured in the BLS data), drop out of the labor force (e.g. transition to retirement or school), move out of the region (e.g. to the South), or shift to employment in another local sector (e.g. wholesale trade or services). In the final case, this shift in workers will impact the equilibrium wage and employment in non-timber sectors in local, comparison areas. There is some evidence of movement of timber industry workers, specifically using unemployment insurance records to track individuals as they find new work in other sectors (Helvoigt et al. (2003)). As in the literature on union wage effects, spillover effects are estimated by looking at the correlation between unionization rates and non-union wages in each local labor market. If the correlation is negative, so non-union wages are lower in markets with higher unionization rates, spillover effects dominate threat effects. In this spotted owl setting, if non-timber wages are lower and employment is higher in local labor market areas that have higher amounts of owl-protection, then spillover effects exist and can potentially be estimated.

How much is due to geographic spillover effects, *i.e.* timber workers in counties with owl protected areas, losing their jobs and taking new jobs in a comparison county? Either they commute farther to work or they move to a county further away, but still in the Pacific Northwest region. If geographic spillovers are large, we can expect to see increased timber production in comparison counties relative to treatment counties. Indeed, timber production did not decrease as much in comparison counties, relative to treatment counties. Estimation results in Table 2.11 indicate that timber harvest overall declined by 63 percent in treatment counties, from 1990-2000, relative to 1975-1989 timber production. For comparison counties, the point estimate is a 14 percent increase, which fits the geographic spillover story, though it is not statistically significant. In both groups of counties, public timber harvest declined dramatically.

Another potentially confounding factor is a recessionary effect which may have additionally contributed to further declines in timber employment in treatment counties. As mentioned earlier, the timber industry is cyclically sensitive, and if treatment counties are relatively more sensitive to business cycle effects, these estimates of employment declines beginning in 1990 may be overly large, once any recessionary-effects are considered. Table 2.12 presents results from timber employment specifications used previously, but only for data *before* owl regulation, so 1975-1989. I rely on the 1981 and 1982 recessions to identify a relative decline in timber employment in treatment counties. Coefficients on the difference-in-differences indicator, $owl * 1980-82$, are mostly positive with one negative coefficient in column (7), and only three specifications are statistically significant. The final specification, in column (9), with year and county indicators and measures of county timberland area implies that timber employment increased by 9.5 percent in treatment counties relative to comparison counties, during the 1981-82 recession. Comparing these results for the early 1980s recession, in pre-owl regulation years (1975-1989) to similar specifications in Table 2.4, in the 1908s recession treatment counties did not experience a noticeable decline in timber employment relative to declines in comparison counties, and may have even seen a slight increase. Therefore, it appears that the cyclicality of timber employment is not a confounding factor for estimates of the labor market impact of spotted owl protection.

2.6 Labor Market Impacts Across Regions

The regulation that established owl-protected areas, primarily in valuable, old-growth forests, may have been restrictive enough to have had impacts beyond the Pacific Northwest and California. The prior section examined local labor market impacts, assuming that the regulation's effects were contained within the region. However, restrictions on federal timber harvest may have been large enough to induce increased production outside of the Pacific Northwest, with relocation or expansion of firms into other timber-producing regions, such as the southern U.S.

The methodology of using treatment and comparison groups assumes that the treatment group embodies all of the regulation's effects, while the comparison group does not. While this framework fits well with partial equilibrium changes, where the regulation affects a single market, in order to consider the possibility that owl protection had impacts outside of the Pacific Northwest, we must adapt this framework to potentially address general equilibrium changes.

A number of papers have found that declines in timber harvest in the Pacific Northwest led the timber industry to shift towards increased production in the southern states, for example: Wear and Murray (2004), Daigneault and Sohngen (2008), and Smith and Munn (1998). Data on employment in the timber industry support this assertion; there is a marked increase in timber employment growth in southern states beginning in 1990.

Searching for appropriate comparison regions for both the treatment counties in the Pacific Northwest, defined as having some owl-protected areas, and for comparison counties as well, implies that timber employment in comparison regions should be highly correlated before the owl regulation, in 1990. I consider a number of alternative timber-producing regions in the U.S. and I also consider timber employment in British Columbia, Canada.

Correlation coefficients for counties in the Pacific Northwest with owl-protected areas, compared to other regions in the U.S. and the Canadian province British Columbia, are highest for British Columbia (0.66), with the time series shown in the bottom panel of Figure 2.4. An estimate of overall timber employment effects in the Pacific Northwest and California, when compared to timber employment in British Columbia, is 7,700 lost jobs[13]. This is substantially smaller than the estimate relying on comparison counties *within* the region (17,600 timber jobs), which is potentially subject to geographic spillovers across county groups. British Columbia may be a better comparison, in terms of limited geographic spillovers, because of the larger barriers to movement across an international border, but similarities in both regions' timber industries.

[13]Regression result from same specification as in Table 2.4, but in levels and with entire Pacific Northwest and California as "treatment" group with British Columbia as comparison group.

2.7 Conclusions

In this paper I use spatial data on northern spotted owl critical habitat areas to distinguish counties within the Pacific Northwest that were directly affected by the Endangered Species Act regulation in 1990, from those counties without owl-protected areas. Approximately 7 million acres of publicly-owned forest land was set aside as owl-protected areas in 1992, and the regulation prevented logging in theses areas. Comparisons of timber employment and earnings per worker in these treated counties, relative to comparison counties within the region between 1975 and 2000, both before and after the regulation in 1990, lead to estimates of declines of 26 percent in timber employment and 2 percent in timber earnings per worker. The variation in size of owl-protected areas by county allows me to estimate the marginal effect of an increase in owl-protected area: I find that for a one percent increase in owl-protected area, by county, we should expect a 0.09 percent decline in timber employment, evaluated at the average size of owl-protected acres. These estimates indicate that the local labor market impacts, for the timber industry, were negative, as expected with a decline in labor demand for the timber industry, but not as large in retrospect, as some predictions had suggested.

Analyses of spillover effects, both geographic, for comparison counties in the region, and sectoral, as unemployed timber workers may have taken jobs in other industries within the same counties that have owl-protected areas yield mixed evidence. While employment changes in comparison counties and non-timber industries in treatment counties are not different from zero, earnings per worker in non-timber industries in treatment counties declined by 5 percent, over 1990 to 2000. Robustness checks include estimates of the impacts across non-timber industries, and across other regions of the U.S. and British Columbia. Taken together, these results indicated that

Northern Spotted Owl protection plausibly led to a small loss of timber earnings per worker and employment in the Pacific Northwest, with larger declines for counties with larger areas of owl-protection.

Table 2.1: **Treatment Counties, Timber Industry (1975)**

County	Timber Employment	Fraction of All Emp.	Fraction of All Earnings
Colusa County, CA	-	-	-
Del Norte County, CA	1,461	0.105	0.129
Glenn County, CA	113	0.007	0.011
Humboldt County, CA	6,520	0.057	0.073
Lake County, CA	80	0.006	0.006
Mendocino County, CA	3,131	0.058	0.081
Shasta County, CA	2,540	0.029	0.036
Siskiyou County, CA	1,946	0.057	0.080
Tehama County, CA	1,167	0.048	0.065
Trinity County, CA	0	0	0
Benton County, OR	1,412	0.022	0.028
Clackamas County, OR	2,236	0.014	0.017
Coos County, OR	4,506	0.065	0.083
Curry County, OR	1,118	0.078	0.116
Deschutes County, OR	2,150	0.042	0.054
Douglas County, OR	8,178	0.081	0.101
Hood River County, OR	630	0.034	0.051
Jackson County, OR	4,662	0.037	0.048
Jefferson County, OR	478	0.044	0.061
Josephine County, OR	2,123	0.050	0.067
Klamath County, OR	4,083	0.065	0.087
Lane County, OR	12,994	0.044	0.056
Lincoln County, OR	774	0.025	0.035
Linn County, OR	5,262	0.054	0.064
Marion County, OR	1,654	0.007	0.008
Multnomah County, OR	3,888	0.003	0.004
Polk County, OR	1,515	0.051	0.067
Tillamook County, OR	767	0.047	0.072
Wasco County, OR	420	0.018	0.023
Yamhill County, OR	1,472	0.034	0.045
Chelan County, WA	716	0.012	0.014
Clallam County, WA	2,375	0.057	0.074
Cowlitz County, WA	5,987	0.061	0.068
Grays Harbor County, WA	4,437	0.069	0.082
Jefferson County, WA	253	0.030	0.041
King County, WA	5,698	0.003	0.004

Continued on next page...

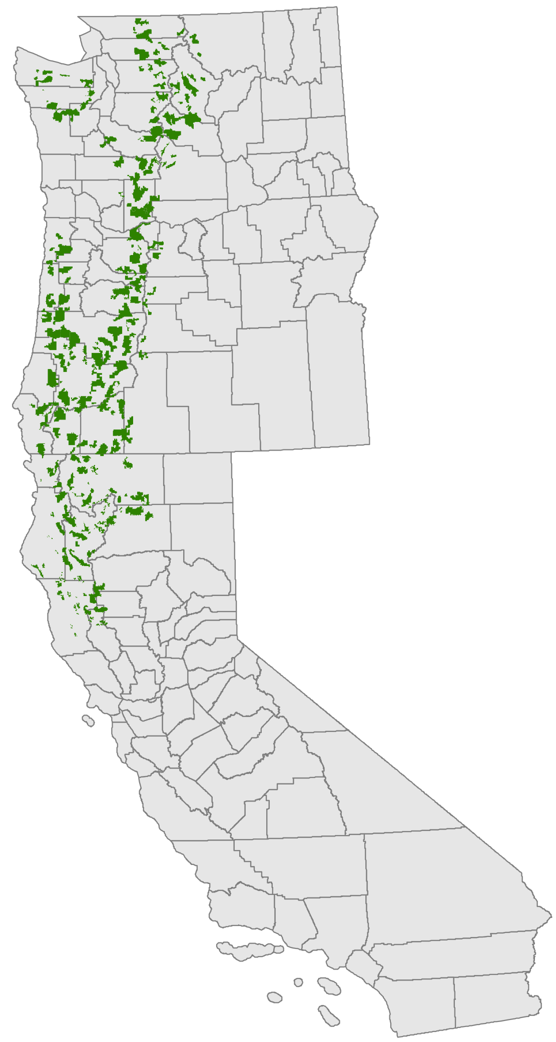
... *Table 2.1 continued*

County	**Timber Employment**	**Fraction of All Emp.**	**Fraction of All Earnings**
Kittitas County, WA	185	0.009	0.011
Klickitat County, WA	701	0.071	0.088
Lewis County, WA	3,340	0.063	0.084
Mason County, WA	1,522	0.084	0.107
Okanogan County, WA	1,187	0.045	0.054
Pierce County, WA	4,652	0.012	0.015
Skagit County, WA	1,166	0.022	0.027
Skamania County, WA	682	0.129	0.144
Snohomish County, WA	4,269	0.019	0.021
Thurston County, WA	1,095	0.010	0.010
Whatcom County, WA	609	0.006	0.007
Yakima County, WA	1,546	0.010	0.014

Source: BLS Quarterly Census of Employment and Wages, county annual averages, 1975, for OR, WA and CA. (N=133 counties)

Note: Treatment counties had some owl-protected areas, 1992-2000. (N= 48)

Figure 2.1: **Map of Owl Critical Habitat in the Pacific Northwest and California**



Source: REO GIS data for 1992 critical habitat areas for the northern spotted owl. Darker, green areas are owl critical habitat. County boundaries for Oregon, Washington and California.

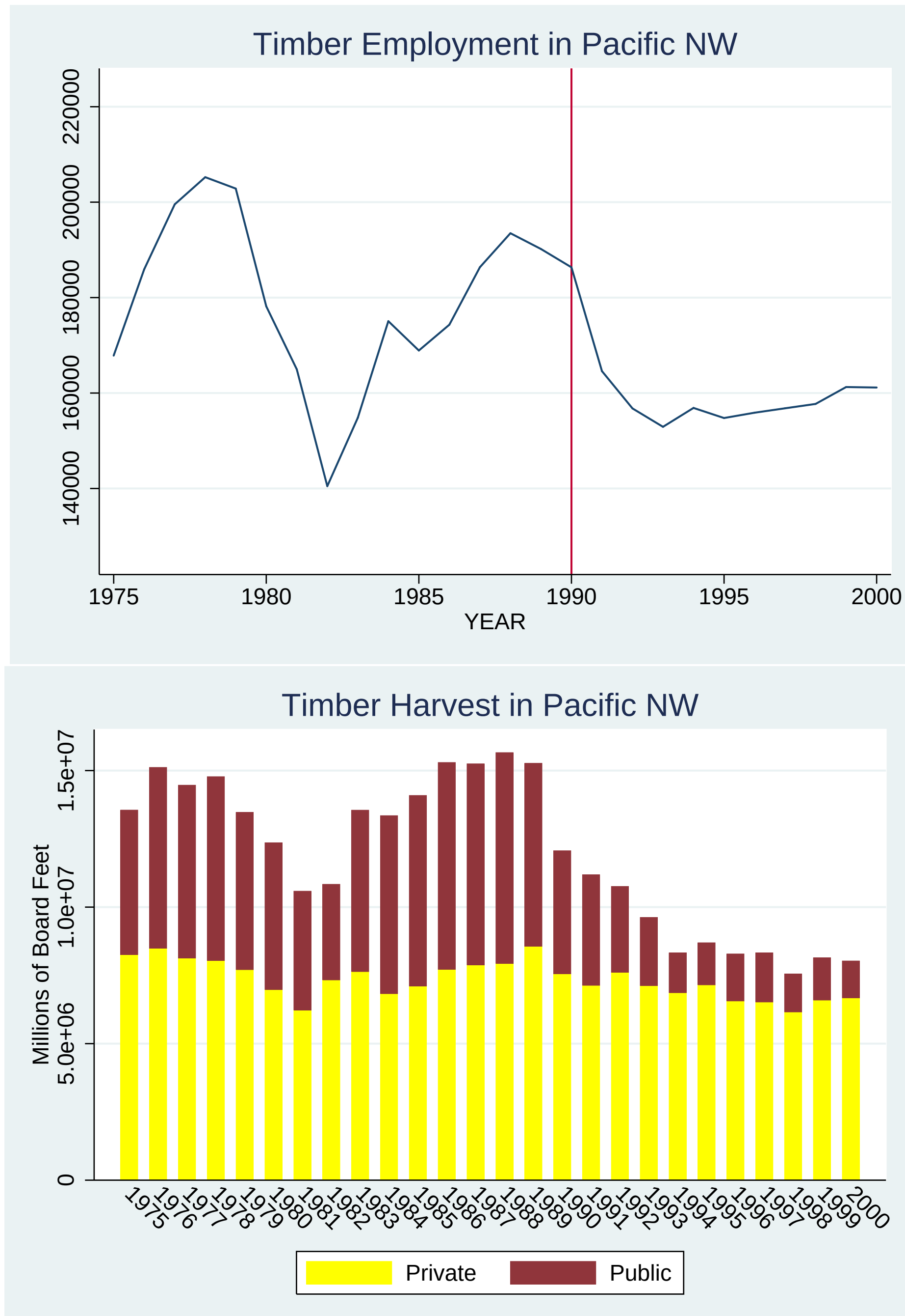


Figure 2.2: **Timber Harvests and Employment in Pacific Northwest, 1975-2000.**

Sources: Timber harvest data is by county and source (public or private owner), for Oregon and Washington, aggregated to the region. Data from the Oregon Dept. of Forestry, and the Washington Dept. of Natural Resources. Timber employment data is also by county, for Oregon, Washington, and California, from the BLS Quarterly Census of Employment and Wages, SIC 24, annual averages.

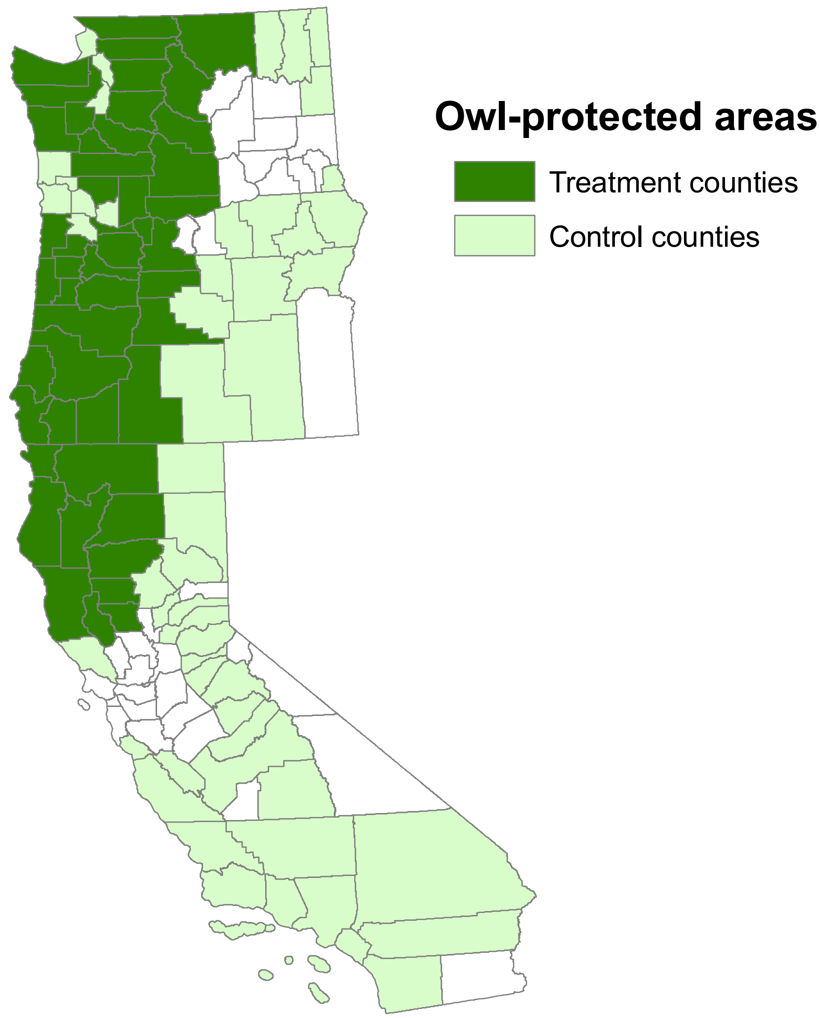
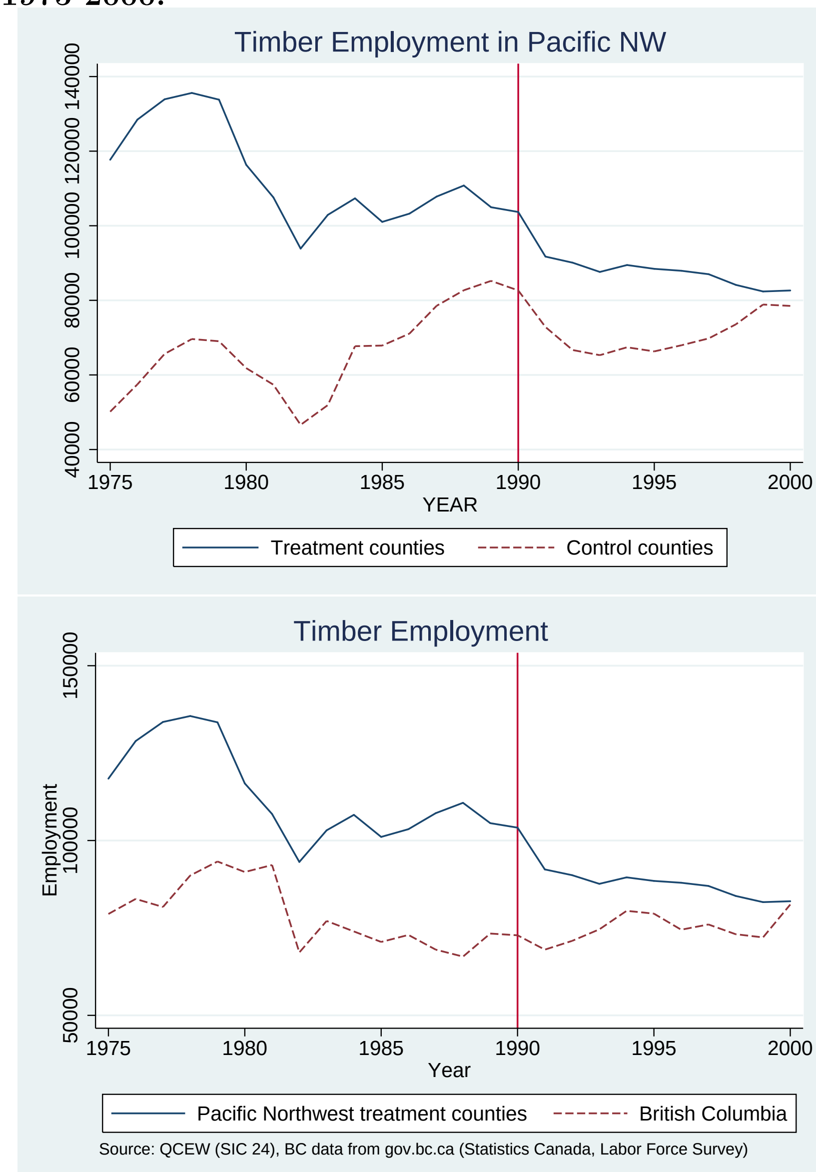


Figure 2.3: **Timber Employment in the Pacific Northwest, by Treatment and Comparison Counties.**

Source: REO GIS data for 1992 critical habitat areas for the northern spotted owl, and author's calculations. Darker green counties have some owl critical habitat areas. Lighter green counties do not have owl critical habitat, but do have some publicly owned timberland. County boundaries for Oregon, Washington and California.

Figure 2.4: **Timber Employment in Pacific Northwest and British Columbia, 1975-2000.**



Sources: Timber employment data is by county for Oregon, Washington, and California, from the BLS Quarterly Census of Employment and Wages, SIC 24, annual averages. British Columbia data from Statistics Canada, Labor Force Survey.

Table 2.2: **Change in Timber Employment, Growth in Earnings and Earnings per Worker — Treatment Counties (1975-2000)**

Average annual levels or growth:	**Treatment counties (with owl protected areas)**
Timber employment (N = 1241)	
pre-owl, 1975-1989	2,391.93
	(88.27)
post-owl, 1990-2000	1,846.95
	(78.87)
Growth in timber employment (N = 1171)	
pre-owl, 1975-1989	-0.01
	(0.01)
post-owl, 1990-2000	-0.03
	(0.00)
Growth in timber earnings (N = 1171)	
pre-owl, 1975-1989	0.04
	(0.01)
post-owl, 1990-2000	-0.00
	(0.01)
Growth in timber earnings per worker (N = 1171)	
pre-owl, 1975-1989	0.05
	(0.00)
post-owl, 1990-2000	0.03
	(0.00)

Source: Author's calculations, BLS Quarterly Census of Employment and Wages data, OR, WA, and CA: 1975-2000. *Note:* Table reports average change in levels of timber employment over the two time periods, within the treatment counties. Table also reports growth in employment or earnings, measured as annual differences in the logarithm of timber employment, earnings, or earnings per worker. Huber-White standard errors in parentheses. **Treatment counties** identifies 48 counties, which had some owl protected areas in 1992.

Table 2.3: **Timber Employment: After - Before Owl Regulation**

Treatment counties only:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post-1990	-0.319	-0.276***	-0.276***	-0.276***	-0.320***	-0.291***	-0.302***	-0.293***
	(0.000)	(0.062)	(0.087)	(0.062)	(0.040)	(0.048)	(0.060)	(0.061)
ln(private timberland)				0.971***		1.980**	0.872***	1.130***
				(0.140)		(0.948)	(0.165)	(0.004)
ln(public timberland)				-0.058		-3.869**	-0.040	-0.007***
				(0.157)		(1.495)	(0.148)	(0.001)
County dummies:			X					X
Number of time periods:	2	2	2	2	26	26	26	26
Number of county-groups:	1	48	48	48	1	1	48	48
Adj. R^2	1.000	0.010	0.977	0.548	0.673	0.690	0.401	0.941
N	2	96	96	96	26	26	1221	1221
Comparison counties only:								
post-1990	-0.011	-0.116	-0.045	-0.135	-0.009	-0.031	-0.040	-0.032
	(0.000)	(0.103)	(0.107)	(0.114)	(0.053)	(0.054)	(0.076)	(0.069)
ln(private timberland)				-0.043		-0.146	-0.132	-0.450***
				(0.197)		(0.392)	(0.165)	(0.000)
ln(public timberland)				0.201		0.688***	0.192	0.005***
				(0.130)		(0.225)	(0.121)	(0.001)
County dummies:			X					X
Number of time periods:	2	2	2	2	26	26	26	26
Number of county-groups:	1	57	57	52	1	1	57	57
Adj. R^2	1.000	0.001	0.966	0.045	0.001	0.189	0.054	0.926
N	2	113	113	103	26	26	1233	1233

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA. Employment in Lumber and Wood Products sector. *Note:* Dependent variable is ln(Timber Employment). Treatment counties have some owl-protected habitat. Comparison counties have non-zero amounts of timber employment and some timberland area. Robust standard errors in parentheses. Pooled OLS results are clustered at the county level, when applicable.

Table 2.4: **Timber Employment: Difference-in-Differences**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
post-1990*owl	-0.308	-0.160	-0.231*	-0.227	-0.311***	-0.311***	-0.289***	-0.278***	-0.261***
	—	(0.120)	(0.138)	(0.141)	(0.052)	(0.073)	(0.084)	(0.091)	(0.092)
owl=1	1.151	1.177***	—	—	1.151***	1.151***	0.444	—	—
	—	(0.279)	—	—	(0.043)	(0.061)	(0.967)	—	—
post-1990=1	-0.011	-0.116	-0.045	-0.049	-0.009	—	—	—	—
	—	(0.103)	(0.107)	(0.111)	(0.053)	—	—	—	—
ln(private				-0.289***			-0.090		-0.286***
timberland)				(0.003)			(0.700)		(0.002)
ln(public				0.906***			0.661		0.896***
timberland)				(0.016)			(0.412)		(0.009)
County dummies:			X	X				X	X
Year dummies:						X	X	X	X
Number of									
time periods:	2	2	2	2	26	26	26	26	26
Number of									
county groups:	2	105	105	100	2	2	2	105	100
Adj. R^2	1.000	0.129	0.974	0.974	0.947	0.984	0.987	0.944	0.946
N	4	209	209	199	52	52	52	2563	2454

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA. Employment for Lumber and Wood Products only (SIC 24).
Note: Dependent variable is ln(timber employment). Pooled OLS results are clustered at the county level, when applicable. Treatment counties, *owl = 1*, had some owl-protected habitat (N=48), while comparison counties had none, but did have non-zero timber employment. Robust standard errors in parentheses, clustered at the county level where applicable.

Table 2.5: **Timber Employment: Size of Owl-Protected Areas in Treatment Counties**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post-1990*ln(owl acres)	-0.114**	-0.114	-0.114	-0.060**	-0.059*	-0.085***	-0.093*	-0.093*
	(0.053)	(0.075)	(0.075)	(0.029)	(0.029)	(0.013)	(0.051)	(0.051)
(post-1990*ln(owl acres))^2	-0.011	-0.011	-0.011	-0.054**	-0.054**	-0.033***	-0.025	-0.025
	(0.037)	(0.052)	(0.052)	(0.020)	(0.020)	(0.006)	(0.032)	(0.032)
post-1990 = 1	-0.269***	-0.269**	-0.269**	-0.267***	—	—	—	—
	(0.077)	(0.109)	(0.109)	(0.044)	—	—	—	—
ln(owl acres)	0.554**	0.700***	0.231***	0.404***	0.404***	0.137***	0.514***	0.402***
	(0.215)	(0.037)	(0.037)	(0.013)	(0.013)	(0.008)	(0.022)	(0.020)
ln(owl acres)^2	0.036	0.255***	0.106***	0.162***	0.162***	0.065***	-0.014	0.167***
	(0.162)	(0.026)	(0.026)	(0.011)	(0.011)	(0.005)	(0.013)	(0.013)
ln(private timberland)			1.165***			0.850***		0.917***
			(0.000)			(0.017)		(0.009)
ln(public timberland)			-0.207***			-0.106***		0.156***
			(0.000)			(0.007)		(0.003)
County dummies:		X	X					X
Year dummies:					X	X	X	X
Number of time periods:	2	2	2	26	26	26	26	26
Adj. R^2	0.143	0.979	0.979	0.118	0.126	0.415	0.951	0.951
N	96	96	96	1221	1221	1221	1221	1221

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA. Employment for Lumber and Wood Products only (SIC 24). *Note:* Dependent variable is ln(timber employment). Pooled OLS results are clustered at the county level, when applicable. *Owl acres* is amount of spotted owl critical habitat in the county; private and public timberland are also at the county-level. Robust standard errors in parentheses, clustered at the county level where applicable.

Table 2.6: **Timber Earnings per Worker: Difference-in-Differences**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
post-1990*owl	-0.023	-0.013	-0.031	-0.037	-0.022**	-0.022	-0.014	-0.023	-0.019
	—	(0.036)	(0.045)	(0.044)	(0.010)	(0.014)	(0.011)	(0.026)	(0.027)
owl=1	0.103	0.107***	—	—	0.102***	0.102***	-0.282**	—	—
	—	(0.028)	—	—	(0.008)	(0.011)	(0.124)	—	—
post-1990=1	0.404	0.386***	0.404***	0.410***	0.405***	—	—	—	—
	—	(0.029)	(0.034)	(0.032)	(0.062)	—	—	—	—
ln(private				0.047***			0.167*		0.047***
timberland)				(0.001)			(0.087)		(0.001)
ln(public				-0.041***			0.155**		-0.042***
timberland)				(0.005)			(0.071)		(0.003)
County dummies:			X	X				X	X
Year dummies:						X	X	X	X
Number of									
time periods:	2	2	2	2	26	26	26	26	26
Number of									
county groups:	2	105	105	100	2	2	2	105	100
Adj. R^2	1.000	0.505	0.915	0.924	0.593	0.998	0.999	0.901	0.902
N	4	209	209	199	52	52	52	2563	2454

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA. Employment for Lumber and Wood Products only (SIC 24).
Note: Dependent variable is ln(timber earnings per worker). Treatment counties, *owl = 1*, had some owl-protected habitat (N=48), while comparison counties had none, but did have non-zero timber employment. Robust standard errors in parentheses. Pooled OLS results are clustered at the county level, when applicable.

Table 2.7: **Non-Timber Employment: Difference-in-Differences**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
post-1990*owl	0.002	0.018	-0.005	0.015	-0.001	-0.001	-0.004	-0.002	0.005
	—	(0.049)	(0.064)	(0.064)	(0.041)	(0.058)	(0.065)	(0.040)	(0.042)
owl=1	0.073	0.233	—	—	0.071***	0.071*	0.369	—	—
	—	(0.333)	—	—	(0.024)	(0.034)	(0.530)	—	—
post-1990=1	0.538	0.512***	0.535***	0.514***	0.542***	—	—	—	—
	—	(0.041)	(0.052)	(0.052)	(0.098)	—	—	—	—
ln(private				-0.809***			-0.361		-0.812***
timberland)				(0.001)			(0.461)		(0.001)
ln(public				1.001***			0.098		1.013***
timberland)				(0.007)			(0.267)		(0.004)
County dummies:			X	X				X	X
Year dummies:						X	X	X	X
Number of time periods:	2	2	2	2	26	26	26	26	26
Number of county groups:	2	105	105	100	2	2	2	105	100
Adj. R^2	1.000	0.025	0.996	0.996	0.583	0.981	0.983	0.994	0.993
N	4	209	209	199	52	52	52	2563	2454

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA.
Note: Dependent variable is ln(non-timber employment), where *non-timber*, by county, is all employment less timber employment. Pooled OLS results are clustered at the county level, when applicable. Treatment counties, *owl = 1*, had some owl-protected habitat (N=48), while comparison counties had none, but did have non-zero timber employment. Robust standard errors in parentheses.

Table 2.8: **Non-Timber Earnings per Worker: Difference-in-Differences**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
post-1990*owl	-0.062	-0.058***	-0.063**	-0.061**	-0.061***	-0.061***	-0.058***	-0.058***	-0.053***
	(0.000)	(0.020)	(0.028)	(0.029)	(0.009)	(0.012)	(0.015)	(0.017)	(0.017)
owl=1	0.017	0.027	—	—	0.016*	0.016	-0.086	—	—
	—	(0.024)	—	—	(0.008)	(0.012)	(0.162)	—	—
post-1990=1	0.509	0.499***	0.504***	0.502***	0.511***	—	—	—	—
	—	(0.015)	(0.021)	(0.021)	(0.068)	—	—	—	—
ln(private timberland)				-0.039***			-0.025		-0.037***
				(0.001)			(0.092)		(0.000)
ln(public timberland)				0.035***			0.106		0.033***
				(0.003)			(0.075)		(0.002)
County dummies:			X	X				X	X
Year dummies:						X	X	X	X
Number of time periods:	2	2	2	2	26	26	26	26	26
Number of county groups:	2	105	105	100	2	2	2	105	100
Adj. R^2	1.000	0.743	0.966	0.966	0.657	0.998	0.999	0.964	0.965
N	4	209	209	199	52	52	52	2563	2454

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA.
Note: Dependent variable is ln(timber earnings per worker), where *non-timber*, by county, is earnings per worker for all sectors less earnings per worker for timber. Robust standard errors in parentheses. Pooled OLS results are clustered at the county level, when applicable.
Treatment counties, *owl = 1*, had some owl-protected habitat (N=48), while comparison counties had none, but did have non-zero timber employment.

Table 2.9: **Employment: DDD**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
post-1990*timber*owl	-0.310	-0.310***	-0.295***	-0.310***	-0.295***	-0.310***	-0.295***
	—	(0.084)	(0.085)	(0.083)	(0.084)	(0.084)	(0.085)
owl=1	0.073	—	—	0.071	0.394	—	—
	—	—	—	(0.329)	(0.323)	—	—
post-1990=1	0.538	0.538***	0.533***	—	—	—	—
	—	(0.035)	(0.038)	—	—	—	—
timber=1	-5.031	-5.031***	-4.799***	-5.031***	-4.799***	-5.031***	-4.799***
	—	(0.235)	(0.226)	(0.233)	(0.225)	(0.236)	(0.227)
post-1990*owl	0.002	0.014	0.019	0.001	0.012	0.015	0.019
	—	(0.045)	(0.047)	(0.064)	(0.066)	(0.045)	(0.047)
timber*owl	1.079	1.079***	0.847***	1.079***	0.847***	1.079***	0.847***
	—	(0.279)	(0.271)	(0.276)	(0.269)	(0.279)	(0.272)
post-1990*timber	-0.549	-0.549***	-0.563***	-0.549***	-0.563***	-0.549***	-0.563***
	—	(0.061)	(0.062)	(0.061)	(0.062)	(0.061)	(0.062)
Timberland dummies:			X		X		X
County dummies:		X	X			X	X
Year dummies:				X	X	X	X
Adj. R^2	1.000	0.932	0.936	0.716	0.718	0.933	0.937
N	8	5126	4908	5126	4908	5126	4908

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA.
Note: Dependent variable is ln(employment). Robust standard errors in parentheses. Pooled OLS results are clustered at the county level, when applicable. Treatment counties, *owl = 1*, had some owl-protected habitat (N=48), while comparison counties had none, but did have non-zero timber employment.

Table 2.10: **Earnings per Worker: DDD**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
post-1990*timber*owl	0.039	0.039	0.038	0.039	0.038	0.039	0.038
	—	(0.025)	(0.026)	(0.024)	(0.025)	(0.025)	(0.026)
owl=1	0.017	—	—	0.016	-0.008	—	—
	—	—	—	(0.023)	(0.025)	—	—
post-1990=1	0.509	0.510***	0.504***	—	—	—	—
	—	(0.012)	(0.013)	—	—	—	—
timber=1	0.241	0.241***	0.264***	0.241***	0.264***	0.241***	0.264***
	—	(0.026)	(0.025)	(0.026)	(0.025)	(0.026)	(0.025)
post-1990*owl	-0.062	-0.061***	-0.055***	-0.061***	-0.055***	-0.060***	-0.055***
	—	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
timber*owl	0.087	0.087***	0.064**	0.087***	0.064**	0.087***	0.064**
	—	(0.030)	(0.029)	(0.030)	(0.029)	(0.030)	(0.029)
post-1990*timber	-0.105	-0.105***	-0.104***	-0.105***	-0.104***	-0.105***	-0.104***
	(0.000)	(0.018)	(0.020)	(0.018)	(0.019)	(0.018)	(0.020)
Timberland dummies:			X		X		X
County dummies:		X	X			X	X
Year dummies:				X	X	X	X
Adj. R^2	1.000	0.639	0.648	0.775	0.789	0.880	0.886
N	8	5126	4908	5126	4908	5126	4908

Source: BLS 1975-2000 annual averages by county for 3 states: OR, WA, CA.
Note: Dependent variable is ln(earnings per worker). Robust standard errors in parentheses. Pooled OLS results are clustered at the county level, when applicable. Treatment counties, *owl = 1*, had some owl-protected habitat (N=48), while comparison counties had none, but did have non-zero timber employment.

Table 2.11: **Timber Harvests, by Treatment and Comparison Counties, and by Public and Private Ownership**

	Treatment Counties			**Comparison Counties**		
	(1) total harvest	(2) private harvest	(3) public harvest	(4) total harvest	(5) private harvest	(6) public harvest
post 1990 = 1	-0.63***	-0.17	-1.15***	0.14	0.23	-0.97**
	(0.09)	(0.12)	(0.15)	(0.12)	(0.20)	(0.36)
ln(private timberland)	0.96***	1.42***	0.44***	0.71***	1. 08***	0.16*
	(0.10)	(0.09)	(0.11)	(0.19)	(0.14)	(0.09)
ln(public timberland)	0.15*	-0.10	0.64***	0.27*	-0.07	0.80***
	(0.08)	(0.10)	(0.11)	(0.14)	(0.11)	(0.11)
Adj. R^2	0.751	0.679	0.653	0.669	0.702	0.629
N	970	988	968	686	695	634

Source: Timber harvest data, by county and owner (public or private), annual, for Oregon and Washington only. Timber harvest in million board feet; timberland in acres. Pooled OLS, 1975-2000; includes year & state effects.

Table 2.12: **Timber Employment: Difference-in-Differences Before Owl Regulation: 1980-82 Recession**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
owl*1980-82	0.116	0.119	0.065	0.109*	0.116**	0.116	-0.038	0.064	0.095**
	—	(0.140)	(0.068)	(0.063)	(0.054)	(0.076)	(0.140)	(0.043)	(0.042)
1980-82=1	-0.219	-0.106	-0.171***	-0.214***	-0.220**	—	—	—	—
	—	(0.069)	(0.057)	(0.050)	(0.082)	—	—	—	—
owl=1	1.128	1.169***	—	—	1.128***	1.128***	0.376	—	—
	—	(0.280)	—	—	(0.053)	(0.075)	(1.616)	—	—
ln(private timberland)				-0.286***			-0.431		-0.279***
				(0.001)			(0.792)		(0.000)
ln(public timberland)				0.830***			1.045		0.837***
				(0.007)			(0.699)		(0.002)
County dummies:			X	X				X	X
Year dummies:						X	X	X	X
Number of time periods:	2	2	2	2	15	15	15	15	15
Number of county groups:	2	105	105	100	2	2	2	105	100
Adj. R^2	1.000	0.170	0.993	0.995	0.953	0.984	0.989	0.964	0.968
N	4	205	205	195	30	30	30	1480	1416

Source: BLS 1975-1989 annual averages by county for 3 states: OR, WA, CA.
Note: Dependent variable is ln(timber earnings per worker), where *non-timber*, by county, is earnings per worker for all sectors less earnings per worker for timber. Robust standard errors in parentheses. Pooled OLS results are clustered at the county level, when applicable. Treatment counties, *owl = 1*, had some owl-protected habitat (N=48), while comparison counties had none, but did have non-zero timber employment. Policy indicator is for recession years: 1980, 1981, and 1982.

CHAPTER III

Parental Health and Children's Educational Outcomes

3.1 Introduction

Health, family relationships, and related economic outcomes have gained more attention in the economics literature, as research has started to focus on the complicated linkages between family health and economic outcomes for individuals. These relationships are mutli-dimensional and complex, and are therefore difficult to identify individually. This paper lays the groundwork for studying the relationship between parents' health and children's human capital accumulation by describing the long-term association between parents' health status and children's educational attainment. We present motivation and evidence of a long-term association between poor parental health and two measures of children's human capital accumulation, focused on higher education: highest grade completed and delays in completing college. We view documenting this association as a first step towards building a more complete picture of the dynamic relationship of health within families and children's human capital accumulation.

Using longitudinal data from the Health and Retirement Study (HRS)[1], we find

[1]Health and Retirement Study. Produced and distributed by the University of Michigan with

evidence of a long-term association between parents' health and their children's educational attainment. The HRS offers a unique resource for studying both parental health and children's education. Parents are interviewed while in their 50s and 60s; the age at which health issues begin to be more prevalent in the population overall. This age-related pattern of a decline in overall heath can vary greatly between individuals. The incidence of health declines is most-varied between the ages of 50 and 70 (Smith (1999), Deaton and Paxon (1998)). By studying parents in this age range, we have a sample with varied health status and a noticeable proportion of parents in relatively poorer health. To classify parents' health we use the HRS question on self-reported health. Individuals are asked to rank their own health on a five-point scale, ranging from "excellent" to "poor" health.

Poor parental health may present difficulties for children at key stages of educational progression. For children, we choose those in the HRS sample who are young enough to still be accumulating more education. In terms of educational attainment we first consider an overall measure: highest grade completed. We also examine the association between having unhealthy parents and delaying college completion[2].

In the literature, educational outcomes have been explained by several factors: ability (as proxied by IQ or AFQT scores), family socioeconomic status, gender, and parents' education. More recently, the literature on education has delved into the area of health effects on educational outcomes, and has demonstrated that a child's own health matters for her educational decisions and achievement. However, in the context of a family, one person's health status or changes in their health status may affect others in the family; either directly, through time spent caretaking, or indirectly,

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[2]Information on college in the Health and Retirement Study (HRS) does not distinguish between two or four year programs. The question asks only about highest grade completed. Therefore, in this paper, the term "college" refers to either two or four year degree programs.

through the loss of financial resources that would otherwise have gone towards a child's education. In this paper, we examine the relationship between parents' health and their children's educational outcomes. Previous work on this question uses non-U.S. data and focuses on mortality (Case and Ardington (2006), Gertler et al. (2004), Lillard and Willis (1994), and Lillard and Willis (1997)). We focus on the association between parental health in the U.S. and children's educational attainment.

Other types of negative shocks can impact the family, and those have also been studied widely. Job loss, healthcare costs associated with parental illness; these can impact the family by reducing their income and/or assets, by drawing down savings. We can track how these negative events impact children's ability to attend and complete their educations, through reduced family financial resources. Children whose parents become ill may face more difficult obstacles than financial – they may lose time spent with a parent who is their biggest role model, mentor, and supporter of their education.

We find significant differences in the long-term associations of mothers' and fathers' declines in health. Dramatic declines in mothers' self-reported health are correlated with lower educational attainment when compared to children of similar socioeconomic backgrounds whose mothers remained relatively healthy. This effect is more noticeable and dramatic for daughters than for sons.

Father's illnesses and declines in self-reported health, on the other hand, appear to only be associated with declines in family financial assets in the long-term. Those declines also explain lower educational attainment for children. Once we control for changes in assets, the effect of a negative health shock for fathers is no longer statistically significant.

Looking at short-term changes, using declines in parental health between waves of the HRS (two-year intervals) leads to generally insignificant results linking changes in health and either educational attainment or delay in completing the first year of college. In terms of highest grade completed, there is some evidence that decreases in parent's health are linked with lower educational attainment, which is more pronounced if the shock occurs at a younger age for the child. In terms of delay, father's health shocks, again at a younger age, have significant effects, but in the opposite sign than expected. So a decline in father's health when the child is between 12 and 15 is associated with *less* of a delay, relative to the average, in completing the first year of college.

The paper proceeds as follows. In the next section we describe the HRS data and our choice of analysis sample. In Section 3.3 we present our empirical approach to documenting the association between parental health declines and children's lower educational attainment. Section 3.4 present results and discusses differences in the association between parents' health and child's educational attainment by age and gender of child. Finally, in Section 3.5 we discuss possible policy implications and draw conclusions.

3.2 Data

The Health and Retirement Study (HRS) is a nationally representative sample of adults around retirement-age, with additional questions about other household members, including spouses and children. The first wave of the study, in 1992, selected adults aged 51 to 61, their spouses of any age, and over-sampled Florida residents, blacks and hispanics. The HRS is one of few nationally representative datasets that contains detailed information on parents' health, information on children's education and transfers between parents and children. In a few waves and in a special 2001 survey, the Human Capital and Educational Expenses Mail Survey, there are questions specifically referring to monetary transfers for education. Questions are asked in each wave about every family member, including children and grandchildren. Interviews take place every two years, and we use the six currently available panels, from 1992 to 2002, enabling us to track parents and their children over a period of 10 years. Because we are examining children's educational outcomes, we utilize a framework where the child in the family is the unit of analysis.

Health is inherently multidimensional. We can think of an individual's health as composed of their physical health, mental health, functional health, disability, etc. This multidimensionality creates some difficulty in measuring health quantitatively. We focus on self-reported health as a measure of global health. We use self-reported health[3] as a measure of baseline parental health in 1992. Self-reported health can be listed as excellent, very good, good, fair, or poor. We also use changes in health: how self-reported health changed from 1992 to 2002, to indicate declines in parent's health.

Household financial status is an important component of both health events and educational decisions. We control for household assets, including home values, parents' self-reported earnings, and whether or not that parent is working. For those who report to not be working, we do not make a distinction between retired, disabled, not in the labor force, or unemployed. This may be an important distinction, if parental labor force transitions effect children's educational attainment. In 1992, about 80 percent of fathers were working, of those who responded to the question, and about 64 percent of mothers worked. By 2002, those numbers fell to about 52 percent for those fathers that responded to the question, and 48 percent for mothers.

The primary focus of the HRS is on retirement-age adults, but we utilize infor-

[3]We utilize RAND data for the HRS health questions, where RAND has cleaned the data to ensure continuity of response (RAND (2004), Servais (2004)).

mation on their children. Our analysis of children's education relies on information collected from parents about their children. Constructing family data, specifically child-level data, from the HRS involves numerous steps and some judgment calls along the way. See Table 2 for a brief outline of our sample selection process and see Servais (2004) for a detailed discussion on assembling HRS family data.

Our focus is on educational outcomes, using either the level of educational attainment or a measure of delay, so we select only those children ages 12 to 22 as of the 1992 interview. Children in this age range are most likely to have not yet completed a college education in 1992, but should have done so, if they were on the college track, by the time our panel ends, in 2002.

There are some issues in tracking these children across waves, because the HRS was not intended to follow the respondents' children over time. There are some known problems with the reuse of individual person-identifiers, particularly for children. We have done some initial analysis to examine the extent of the possible reuse problem, and conclude that fewer than 3% of our sample are at risk, and later analyses were done on both the entire selected sample and a subset where these 3% were removed. There were no significant differences between the two.

In terms of sample selection, we further refine the sample of children to control for family composition. To eliminate the possibility of confounding effects of both health and family shocks on children's educational outcomes, we restrict the sample in 1992 to only those children with two married parents, who both report that the child is their natural child. See Table 3.1 for a brief overview of the steps involved in sample selection. This reduces our sample size to 2,492 observations. The implications of this restriction will be discussed in the following section on methods.

If parents separate, the HRS records separate parental records for each child. This results in multiple observations on a child in a single wave, increasing our sample from

3,969 to 4,525. Currently, we resolve this issue by flagging those observations, and performing the analysis both with and without those duplicate observations. When restricted, we use the first observation listed, which is for the primary respondent as of 1992. In the results that follow, we eliminate flagged observations from our sample.

Table 3.2 presents summary information on parents and children in our sample. We discuss important aspects of the data in sections below, for parents and children separately. Child's educational attainment is recorded as their highest grade completed. This question is asked initially of parents whose children are older than 18 in 1992, and reported in years of child's education. From 1996 onwards, completed education is in terms of degrees with allowances to report in years if less than high school, and an option to report "some college". In later waves, child's highest grade completed is only asked if there has been a change in educational status of that child, and the child is either new to the household (and therefore excluded in our analysis) or between the ages of 18 and 30. This leaves some values coded as missing in 2002, even though educational attainment for that child was reported in an earlier wave, and most likely has not changed. All of our selected children are below the top age-limit in the eligible range, and may be assumed to have valid answers to this question. Therefore, we construct our measure of highest grade completed for the child, as of 2002, as the maximum value reported for each child between 1992 and 2002. Note that there are only a few cases where the highest grade completed falls in a later wave and we flagged them. There are only 2,464 non-missing observations, and the mean is 13.7, so that the average child in the sample has some education beyond high school. A value of zero indicates "no formal education".

Our measure of delay is for the selected sample of children who eventually complete a college degree or higher. We aim to identify those children who are delaying finishing their first year of college, and are not on track to graduate at the expected age of

22. Delay takes on the value of 1 if the child has not yet completed their first year of college between the ages of 19 and older, and zero otherwise. If the child is 18 or younger, delay is coded as missing because they are not age-eligible.

Other educational outcomes of interest are the following three variations on highest grade completed: an indicator for less than high school, an indicator for more than high school, and an indicator for a college degree or greater. In 2002, our selected sample of children ranges in age from about 22 to about 32; 65% of them have completed high school or a bit more, and 33% of them have a bachelor's degree or graduate degree.

The next set of variables focuses on the parents' information: race, earnings, education, age, and health. Education for HRS respondents is reported in 5 categories: less than high school, a GED or equivalent, high school graduate, some college, and college and above. The average parent has a high school education. The average age of fathers in this sample is 55 in 1992, which is in the middle of the range of 51 to 61 for HRS respondents. Mothers are slightly younger; their average age is 50.

We focus on self-reported health as a general measure of parents' health. About 79% of fathers and 82% of mothers rate their health in 1992 as "good" or better. In terms of changes in parents' self-reported health, we first ook at the long-difference: health changes between the first and last waves (1992 and 2002). Next we utilize the panel structure of the data to observe delays in educational attainment that are associated with declines in parental health over a shorter time frame. The indicator variable for a health decline, for fathers or mothers, is determined by self-reported health between 1992 and 2002, and equals 1 if that decline in health is larger than one category. Table 3.2 shows that about 12% of fathers experienced a negative change larger than 1 category, 3% larger than 2 categories, and 0.5% of the changes were larger than 3 categories. Mothers are similar, in that 11% had a change larger than

1 category, 3% larger than 2, and 0.2% larger than 3, between 1992 and 2002.

We also construct a measure of health declines on a scale from 0 to 10, with increasing severity. A value of 0 indicates no decline in self-reported health of the parent between waves. A value of 1 indicates that self-reported health declined one category: from "excellent" to "very good". A value of 2 is for a decline from "very good" to "good", and so on. Values 1 through 4 represent declines of only one category; values 5-7 for two categories; 8 and 9 are for three categories. A value of 10 represents the largest possible decline: from "excellent" to "poor", which is four categories.

3.3 Empirical Analysis

The reduced-form model we are estimating is as follows:

$$y_i = x_i\beta + s_i^f\gamma^f + s_i^m\gamma^m + \epsilon_i \tag{3.1}$$

where y_i is highest grade completed for child i in 2002, x_i is a set of explanatory variables, including a constant, child's age in 1992, gender, number of siblings, an indicator for firstborn, and indicators for parents' baseline health in 1992. s_i^f is an indicator for a decline in father's health from 1992 to 2002, for child i. Likewise, s_i^m is an indicator for a decline in mother's health. So γ^f and γ^m are the coefficients of interest, in linking a decline in parent's health to a reduction in educational attainment. In the estimation, standard errors are clustered by household because the variation in both s_i^f and s_i^m are by household, even though y_i varies by individual.

Table 3 presents a first look at the association between parents' health and children's educational outcomes. Each column of the table reports results from a separate OLS regression, with robust standard errors presented in parentheses. Included in the last three specifications, columns (4)-(6), are controls for household and parent demographics: age, race, education, earnings, and assets. In what follows, we control for children's ages in order to separate the differences in educational attainment that are potentially attributable to a parent's declines in health from general differences between children due to their age. Within this age range of 22 to 32, older children should have completed more schooling than relatively younger children.

Column (1) in Table 3.3 presents the results of a baseline linear regression of child's educational attainment as of 2002 on the following independent variables: an indicator for the child's gender, ages of the child, father, and mother, father's and mother's baseline health (using the different categories in self-reported health: excellent, very good, good, fair, and poor, with "excellent" as the excluded category), and indicators for declines in mother's or father's health of more than one category. There are 1420 observations used of a possible 1720 (as reported in Table 3.2, non-missing observations for fathers' health changes between 1992 and 2002)[4]. This specification has a coefficient of 13.25 on the constant, which is significant at the 1% level. This implies that the average male child should expect to receive 13.25 years of education, if both his parents are of average age and report being in excellent health in 1992 in our selected sample. Relative to "excellent" health, a father's report of "fair" health leads to one less year of education (at a 1% significance level) and "poor" health predicts 1.77 fewer years. Mother's self-reported health is also negatively related with educational attainment and categories are significantly different from reporting "excellent" health. The coefficient on the indicator for child's gender implies that

[4]Observations that have been flagged as having child's gender change over the panel, or have duplicate observations for a single child have been dropped. Results are not sensitive to removal of these cases.

daughters complete about 0.4 more years of education than sons. This is significant at the 1% level, and remains so when we add additional demographic controls in columns (4) through (6). The following controls are used in columns (4) through (6), but are not reported in the table. Father's age in 1992 is insignificant, but having controlled for it, mother's age is significant at the 1% level. Parent's race is not significant, and neither are parents' earnings. Children whose fathers and mothers have graduated from high school or have additional education are more likely to attain higher levels of education themselves. Coefficients for these variables are not reported, but all three higher education dummies for both the father and mother are significant at the 1% level, and also remain significant through our other specifications. Parental education appears to have a non-linear, positive relationship with child's educational attainment. Indicators for asset quartiles are all significant at the 1% level, in regards to the excluded category of the lowest asset quartile. Children whose families are wealthier are more likely to achieve higher levels of education.

When we separate the sample by child's gender, as in columns (2) and (3), and again in (5) and (6), parental health status and health changes have different impacts on daughters and sons, with daughters showing the greater decline in educational attainment, particularly for declines in mother's health. A decline in father's health is associated with lower attainment for both daughters and sons, but daughters experience an additional decline of 0.35 years, when controls are included. There is a more dramatic result associated with declines in mother's health, where sons show a significant decline of 0.6 years of educational attainment, while daughters experience a decline of about one year, both relative to their same-gender peers whose parents' health did not decline.

For illustrative purposes, we can imagine that parental health declines may affect children's educational attainment through two pathways: the high financial cost of illness reduces the family's assets, and the high time cost of illness reduces the time that the parent can spend with their child. We can examine the impact of health shocks on each of these two measures separately, using the financial information available in the HRS, and proxy information on time-spent by family members during parental illness. In Table 3.4, we present results for linear regressions of household financial status on parental health status and health changes.

In Table 3.4 we examine the relationship between parental health and household financial assets. The relationship between financial assets and health is complicated and intertwined. Poor health will have a negative impact on family assets if the illness is serious or lengthy enough to require costly medical care, generally not fully covered by health insurance. Conversely, less wealth may lead to relatively poorer health, due to lack of preventative medical care. This paper is not concerned with causality for this pathway, but is concerned with endogeneity between household assets and parental health in terms of determining child's educational attainment. We examine the impact of parental health changes on children's educational attainment, and therefore need to address the part of this effect that is due to changes in financial assets within the household.

Table 3.4 establishes that there is a significant relationship between relatively poor health and a decline in the growth rate of household financial assets. Relatively poor baseline health for fathers and mothers is significantly related to declines in the growth rate of household financial assets, as seen in column (1). Fathers who report their health as being "good" or worse in 1992 are in households that have a decline in the growth rate of assets 10 years later. A father who reports being in "poor" health in 1992 would expect to have a one percent decline in the growth rate of household financial assets ten years later, in 2002. Baseline health is significant for fathers, but changes in self-reported health are not statistically significant. Both baseline health and changes in health for mothers are significantly related to lower growth rates household assets in 2002, and the effects of both are larger than for fathers. Households with a mother who reports "poor" health in 1992 should also experience a marginal decline of financial asset growth of 1 percent, as with fathers. Additionally, those households that have a mother whose health declines have an additional decline in the growth rate of assets of 0.8%. Adding controls for age, race, education, etc., removes any significance for father's health or health change. However mother's health and health change are still significantly related to declines in the growth rate of household financial assets, as seen in columns (4) and (6). Evidence of a strong relationship between parental health, particularly for mothers, and household financial assets calls for some way of instrumenting for parental health in our specification of interest: educational outcomes of children.

We use self-reported health as a global measure of parent's health, but it is likely reported with some error. Ideally, we'd like to use parent's true health, but that is not observed. We can define self-reported health as equaling true health plus some error term. If we use self-reported health, instead of true health, we then introduce another source of error in our specification. In equation (3.1), because s_i^f and s_i^m are constructed using self-reported, not true, health, we will have a biased and inconsistent estimate of our coefficients of interest: γ^f and γ^m. If the measurement error on self-reported health is classical, we can use an instrumental variables framework to resolve this issue of a downward-bias in the OLS estimator.

In the following sections, as we examine the extent to which a decline in the health of a parent is associated with lower educational attainment, we control for household socioeconomic status in order not to attribute poorer outcomes to parents' declines in health, when in fact those poorer outcomes are actually attributable to lower household assets and income. We also separately run the specifications for only mothers and their declines in health and again for fathers. Interestingly, the effects of health declines of fathers on children's educational attainment disappear once we control for assets and other demographic controls, indicating that the financial path is what relates father's health changes to their children's educational outcomes. But for mothers, their health declines still have a significant association with reduced educational attainment, even controlling for family finances and other demographic characteristics.

Looking at ten-year changes most likely masks effects that can happen over shorter spans of time. We now consider the possibility that a decline in parent's health may not result in a permanent decrease in educational attainment, but instead may cause children to delay their education. By focusing only on a 10-year change, we cannot observe such delays. In this section, we utilize data in the full HRS panel and employ panel estimators to identify the possible effects of parental health on delays in educational attainment.

We utilize changes over 2-year periods, between HRS interviews, to estimate the dynamic effects of a parental health shock. We can observe whether children of comparable age and educational paths delay their educational attainment or enrollment when their parent experiences a decline in health. Earlier, we described our constructed variable for delay in completing the first year of college, for those children who eventually graduate from college.

Cross-tabulations of parental health shocks and whether the child has completed at least one year of college, by child's age cohort, indicate that children whose parents experience health declines do, in fact, delay education. Focusing on all 20-year olds in our panel (745 observations), across all cohorts, there is a significant difference in average values for delay. 498 of those 20 yr olds eventually complete college, and 24 of them have at least one parent that experiences a health decline of more than one category: 50% delay their first year of college. For the remaining 474, only 30% delay. This gap disappears for all other ages. The specifications in Tables 6,7, and 8 utilize panel data to examine these short differences.

We estimate the following reduced-form specification:

$$y_{it} = x_{it}\beta + s_{it}^{f}\gamma^{f} + s_{it}^{m}\gamma^{m} + w_t + \epsilon_{it}$$

where y_{it} is either highest grade completed as of year t for child i, or an indicator for delay: $y_{it} = 1$ if child i has completed 13 or more years of schooling as of year t, given that child i will eventually graduate from college, and is 0 otherwise. x_i is a set of explanatory variables, including child's age, age-squared, gender, number of siblings, an indicator for firstborn, and indicators for parents' baseline health. w_t are dummies for each wave. s_i^f is an indicator for a decline in father's health between HRS waves, i.e. from $t-1$ to t, for child i. Likewise, s_i^m is an indicator for a decline in mother's health. So γ^f and γ^m are the coefficients of interest, in linking a decline in parent's health to a reduction in educational attainment. In the estimation, standard errors are clustered by household.

Table 3.5 presents estimates similar to those in Tables 3.3, in that the first column includes information on both parents and for all children. Columns (2) and (3) reduce the sample to daughters and sons only, respectively.

The top section of Table 3.5 shows results from the pooled OLS estimator, on the whole sample of HRS waves from 1992 to 2002. The dependent variable is highest grade completed, as before, in Table 3.3. Here, however, highest grade completed is for each wave of the panel, rather than just the last wave, as previous. Explanatory variables include an indicator for child's gender, child's age and age-squared, number of siblings, indicator for firstborn, indicators for father's and mother's health (level in each wave), and indicators for changes in parent's health. Standard errors are clustered by household. Coefficients for only selected variables are presented. In the full sample, shown in column (1), daughters are likely to complete 0.4 more years of education than sons, all else equal, and this estimate is significant at the one-percent level. Declines for parents' health, both in terms of shocks (more drastic health changes) and our more expansive definition of health changes, on a scale from 0 to 10, are insignificant in these pooled specifications.

The bottom portion of Table 3.5 repeats the above analysis, but uses a different definition of health changes, constructed on a scale of 0 to 10, with 10 being the largest decline possible in self-reported health, from "excellent" to "poor". As with the health shock measure, results for declines in parental health are generally not different from zero.

Tables 3.6 and 3.7 present results from fixed effects specifications, with household fixed effects, where the household is notated by j. If there are unobserved characteristics of households that may be important in determining educational attainment or delay, we can eliminate them from the analysis by differencing them out of the specifications. The fixed-effect model we are estimating is as follows:

$$y_{ijt} = x_{ijt}\beta + s^f_{ijt}\gamma^f + s^m_{ijt}\gamma^m + w_t + \epsilon_{ijt}$$

where y_ijt is the household de-meaned value for either highest grade completed for child i at time t, or an household de-meaned value for delay in completing the first year of college, if that child eventually graduates from college. x_i is a set of explanatory variables, including child's age, age-squared, gender, number of siblings, an indicator for firstborn, and indicators for parents' baseline health in each wave. w_t are dummies for each wave. s^f_i is an indicator for a decline in father's health between HRS waves, i.e. from $t-1$ to t, for child i. Likewise, s_i^m is an indicator for a decline in mother's health. So γ^f and γ^m are the coefficients of interest, in linking a decline in parent's health to a reduction in educational attainment. In the estimation, standard errors are clustered by household. There are some siblings in the sample, who obviously have the same parents and experience the same changes in parental health.

Results in Table 3.6 show estimates that are not significantly different from zero. The fixed-effects model does not appear to fit the data very well, as partly indicated by the adjusted R-squared values, which are very close to zero. We might suspect a poor fit with highest grade completed as the dependent variable, as it is not supposed to ever decrease. Using the value of each child's difference between current highest grade completed and their household average level, for all siblings, mechanically results in lower values earlier in the panel and then increasing differences towards the end. However, the variable for delay has been coded as {0,1}, and while children in the sample are 19 and older and eventually complete college, we can observe either value. But even here, the fit is poor.

Table 3.7 introduces age-shock interactions to the specifications in Table 3.6. Presumably, effects of parental health declines may vary greatly, depending on how old the child is at the time. Younger children may bear more of the burden of the shock if they lose time with a parent who is a stong educational mentor. On the other hand, relatively older children may choose to delay college for a while in order to spend more time with the parent, work to replace the parent's lost earnings, or both. Table 3.7 includes age-health shock interactions for both father's and mother's health declines. We specify age-ranges of 12-15 and 16-19 and 20 and older, and interact those dummies with the health shock measure. The excluded category is children 20 and older. At these ages, there should be less of an effect of a health shock because students are relatively close to finishing their educational paths, relative to younger children. Results in column (1) indicate substantial effects of both father's and mother's health shocks, particularly for children at younger ages. In the top panel, with highest grade completed as the outcome, the coefficient of a father's health shock is 0.581 and significant at the 1-percent level. Though it is positive instead of the being negative, as expected, in order to interpret the marginal effect we need to add this to the coefficient on the age-category of interest. For example, if the shock occurs when the child is 12-15, the actual effect is 0.581 - 0.843 = -0.262 years of completed education. This estimate is very close to the long-difference estimate in column (1) of Table 3.3, which is -0.275 years of completed education. In Table 3.7, column (2) shows a large effect, -1.21 years, for daughters aged 12-15 if the mother has the health shock.

The bottom panel of Table 3.7 uses delay as the dependent variable, and the only significant coefficient is for a father's health decline, particularly for younger sons. In column (3), for sons only, a decline in father's health when the son is age 12-15 is related to a 7% decline in the probability of delaying the first year of college.

Remarkably, sons may bear more of the burden over the short term in terms of educational outcomes when it comes to parental health declines. That is, they are less likely to delay completing their first year of college, when the health of their father declines at a younger age. Earlier, when examining the long differences, i.e. changes over a 10-year period, we found that daughters experienced larger impacts of health declines, in terms of lower grade completion. Results from 10-year changes looking at the level of educational attainment indicate that daughters achieve slightly lower levels of completed education than sons, given a decline in mother's health.

3.4 Conclusions

In this paper, we propose that health events within the family can negatively effect a child's educational attainment. Using HRS data, we find that there are significant effects of health shocks for educational attainment. Results indicate that effects of health shocks are larger if the mother experiences the shock rather than the father. Importantly, daughters appear to be effected more than sons by a mother's decline in health. Overall, we document a negative relationship between changes in parent's health and the child's educational attainment.

Table 3.1: **Sample Selection**

	Observations	Description
Step 1:	24,697	All children in wave 1 of HRS (1992)
Step 2:	3,969	Children ages 12 to 22 in wave 1 of HRS (1992)
Step 3:	2,492	Children with married, natural parents (1992)
Step 4:	2,464	Children with education information (2002)
	2,381	Children with father's health information (2002)
	2,270	Children with mother's health information (2002)

Table 3.2: **Descriptive Statistics**

Variable	Observations	Mean	Std. Dev.	Min	Max
Child:					
highest grade completed (2002)	2464	13.70	2.91	0	20
highest grade completed (panel)	12103	12.44	3.99	0	20
delay first year of college (panel)	7464	0.15	0.35	0	1
less than HS = 1 (2002)	2464	0.09	0.29	0	1
more than HS = 1 (2002)	2464	0.65	0.48	0	1
BA or higher = 1 (2002)	2464	0.33	0.47	0	1
age (1992)	2492	18.68	2.87	12	22
female = 1	2492	0.49	0.50	0	1
Father:					
age (1992)	2381	55.07	4.38	41	76
health = "excellent" (1992)	2381	0.22	0.42	0	1
health = "very good" (1992)	2492	0.24	0.43	0	1
health = "good" (1992)	2381	0.32	0.47	0	1
health = "fair" (1992)	2381	0.13	0.34	0	1
health = "poor" (1992)	2381	0.07	0.26	0	1
health change >1 category (2002)	1720	0.12	0.32	0	1
health change >1 category (panel)	12966	0.04	0.20	0	1
health change > 2 categories (2002)	1720	0.03	0.17	0	1
health change > 3 categories (2002)	1720	0.005	0.07	0	1
health change: 0 to 10	8373	0.87	1.76	0	10
Mother:					
age (1992)	2423	50.46	4.77	32	66
health = "excellent" (1992)	2423	0.27	0.45	0	1
health = "very good" (1992)	2423	0.2618	0.44	0	1
health = "good" (1992)	2423	0.29	0.45	0	1
health = "fair" (1992)	2423	0.12	0.32	0	1
health = "poor" (1992)	2423	0.05	0.22	0	1
health change > 1 category (2002)	1933	0.11	0.31	0	1
health change > 1 category (panel)	12966	0.03	0.18	0	1
health change > 2 categories (2002)	1933	0.03	0.16	0	1
health change > 3 categories (2002)	1933	0.002	0.05	0	1
health change: 0 to 10	8970	0.73	1.57	0	10

Note: Entries with (1992) or (2002) are from the long-term effect sample, which looks only at the 10-year change. All other entries, labeled as (panel) refer to the panel data, with information on 6 waves of the HRS. Health change is also referred to as health decline, and is an indicator for a decline of more than one category in self-reported health from 1992 to 2002. Observations where child's gender changes over the panel or duplicate observations of the same child were removed.

Table 3.3: **Highest Grade Completed (2002) and Parental Health**

	(1)	(2) daughters	(3) sons	(4)	(5) daughters	(6) sons
Child:						
female = 1	0.398			0.379		
	(0.117)**			(0.106)**		
age (1992)	0.109	0.121	0.098	0.090	0.114	0.069
	(0.028)**	(0.035)**	(0.039)*	(0.026)**	(0.033)**	(0.036)
no. of siblings	-0.113	-0.133	-0.101	0.076	0.065	0.104
	(0.098)	(0.117)	(0.127)	(0.087)	(0.099)	(0.122)
firstborn = 1	0.118	-0.016	0.240	0.066	-0.082	0.202
	(0.150)	(0.206)	(0.217)	(0.144)	(0.201)	(0.202)
Father's health:						
"very good" (1992)	-0.249	-0.292	-0.221	-0.143	-0.111	-0.215
	(0.188)	(0.225)	(0.261)	(0.167)	(0.207)	(0.236)
"good" (1992)	-0.835	-0.869	-0.836	-0.308	-0.366	-0.345
	(0.202)**	(0.267)**	(0.253)**	(0.183)	(0.252)	(0.232)
"fair" (1992)	-1.021	-1.227	-0.794	-0.382	-0.675	-0.180
	(0.298)**	(0.395)**	(0.379)*	(0.268)	(0.359)	(0.362)
"poor" (1992)	-1.773	-1.711	-1.965	-0.841	-0.829	-0.892
	(0.293)**	(0.379)**	(0.430)**	(0.297)**	(0.393)*	(0.429)*
decline (1992 - 2002)	-0.275	-0.499	-0.035	-0.085	-0.348	0.082
	(0.235)	(0.317)	(0.297)	(0.208)	(0.293)	(0.249)
Mother's health:						
"very good" (1992)	-0.291	-0.229	-0.344	-0.107	-0.050	-0.189
	(0.169)	(0.219)	(0.232)	(0.149)	(0.188)	(0.215)
"good" (1992)	-0.899	-0.973	-0.814	-0.158	-0.337	-0.009
	(0.189)**	(0.234)**	(0.261)**	(0.178)	(0.222)	(0.261)
"fair" (1992)	-1.199	-1.298	-1.086	-0.098	-0.350	0.156
	(0.265)**	(0.323)**	(0.393)**	(0.263)	(0.339)	(0.393)
"poor" (1992)	-1.439	-1.730	-1.076	-0.267	-0.544	-0.001
	(0.415)**	(0.456)**	(0.562)	(0.343)	(0.434)	(0.450)
decline (1992 - 2002)	-1.388	-1.591	-1.208	-0.795	-1.042	-0.621
	(0.286)**	(0.362)**	(0.382)**	(0.246)**	(0.290)**	(0.363)
Both parents' health:						
decline (1992-2002)	-0.694	-0.760	-0.558	-0.524	-0.537	-0.241
	(1.264)	(1.261)	(1.537)	(1.236)	(1.233)	(1.467)
Constant	13.251	13.597	13.304	8.540	8.735	8.894
	(0.546)**	(0.637)**	(0.794)**	(0.981)**	(1.292)**	(1.333)**
Controls				X	X	X
Obs.	1420	702	718	1420	702	718
Adjusted R^2	0.14	0.18	0.10	0.28	0.31	0.25

Note: OLS estimates with robust standard errors in parentheses; clustered by household. Controls include parents' ages, education, race, earnings, and family assets.

Table 3.4: **Household Financial Assets (log change: 1992-2002)**

	(1)	(2)	(3)	(4)	(5)	(6)
Father:						
age				-0.004	0.012	
				(0.020)	(0.017)	
health:						
"very good"	-0.215	-0.306		-0.029	0.029	
	(0.169)	(0.169)		(0.158)	(0.157)	
"good"	-0.592	-0.862		-0.260	-0.304	
	(0.161)**	(0.169)**		(0.164)	(0.168)	
"fair"	-0.816	-1.353		-0.350	-0.460	
	(0.263)**	(0.252)**		(0.273)	(0.254)	
"poor"	-1.090	-1.622		-0.038	-0.615	
	(0.314)**	(0.332)**		(0.236)	(0.587)	
decline (1992-2002)	-0.310	-0.531		1.071	2.306	
	(0.188)	(0.204)**		(2.938)	(3.020)	
Mother:						
age				0.041		0.031
				(0.018)*		(0.014)*
health:						
"very good"	-0.514		-0.621	-0.297		-0.517
	(0.154)**		(0.154)**	(0.152)		(0.146)**
"good"	-1.004		-1.217	-0.400		-0.810
	(0.166)**		(0.171)**	(0.175)*		(0.173)**
"fair"	-1.762		-2.025	-1.160		-1.411
	(0.282)**		(0.288)**	(0.303)**		(0.274)**
"poor"	-1.003		-1.394	-0.010		-0.540
	(0.308)**		(0.270)**	(0.328)		(0.292)
decline	-0.818		-0.956	3.453		4.497
	(0.236)**		(0.234)**	(2.807)		(2.448)
Constant	12.567	12.066	12.292	8.702	9.365	9.640
	(0.146)**	(0.127)**	(0.115)**	(1.076)**	(0.953)**	(0.736)**
Controls				X	X	X
Obs.	1054	1111	1054	913	958	1054
Adjusted R^2	0.18	0.08	0.15	0.28	0.23	0.24

Note: * significant at 5% and ** significant at 1%
OLS estimates with robust standard errors in parentheses clustered by household. Controls include parents' ages, education, race, and earnings. Observations where child's gender changes over the panel or duplicate observations of the same child were removed.

Table 3.5: **Educational Attainment and Changes in Parents Health: Pooled OLS Estimates**

		(1)	(2)	(3)
Highest grade	completed:		daughters	sons
Child:	female=1	0.409		
		(0.103)**		
Father:	health change (0-10)	0.030	0.052	0.030
		(0.022)	(0.031)	(0.030)
Mother:	health change (0-10)	0.009	-0.044	0.047
		(0.023)	(0.031)	(0.030)
Adjusted R^2		0.44	0.44	0.51
Obs.		7540	3739	3801
Highest grade	completed:		daughters	sons
Child:	female=1	0.408		
		(0.098)**		
Father:	health shock	-0.204	-0.114	-0.218
		(0.157)	(0.223)	(0.202)
Mother:	health shock	-0.285	-0.404	-0.252
		(0.175)	(0.226)	(0.223)
Adjusted R^2		0.38	0.38	0.43
Obs.		9065	4476	4589
Delay:			daughters	sons
Child:	female=1	-0.024		
		(0.013)		
Father:	health change (0-10)	0.005	0.002	0.008
		(0.003)	(0.004)	(0.005)
Mother:	health change (0-10)	0.001	0.001	-0.000
		(0.003)	(0.004)	(0.005)
Adjusted	R-squared	0.06	0.06	0.07
Obs.		5230	2738	2492
Delay:			daughters	sons
Child:	female=1	-0.028		
		(0.012)*		
Father:	health shock	0.018	-0.003	0.041
		(0.022)	(0.028)	(0.033)
Mother:	health shock	-0.017	-0.031	-0.001
		(0.023)	(0.030)	(0.036)
Adjusted R^2		0.06	0.07	0.06
Obs.		6671	3473	3198

Note: Robust standard errors in parentheses. * significant at 5%, ** significant at 1%. Controls include parents' age, race, education, assets, dummies for the 5 self-reported health categories.

Table 3.6: **Educational Attainment and Parents Health: Fixed Effects**

		(1)	(2)	(3)
Highest grade	completed:		daughters	sons
Child:	female=1	0.198		
		(0.128)		
Father:	health change (0-10)	0.051	0.059	0.049
		(0.022)*	(0.033)	(0.029)
Mother:	health change (0-10)	0.044	0.003	0.053
		(0.023)	(0.032)	(0.031)
Adjusted R^2		0.32	0.29	0.44
Number of HH		1244	740	764
Obs.		7540	3739	3801
Highest grade	completed:		daughters	sons
Child:	female=1	0.243		
		(0.118)*		
Father:	health shock	-0.040	-0.076	0.087
		(0.152)	(0.228)	(0.189)
Mother:	health shock	-0.217	-0.235	-0.332
		(0.170)	(0.230)	(0.237)
Adj. R^2		0.27	0.25	0.34
Number of HH		1283	763	791
Obs.		9065	4476	4589
Delay:			daughters	sons
Child:	female=1	-0.039		
		(0.018)*		
Father:	health change (0-10)	-0.002	-0.002	-0.000
		(0.003)	(0.005)	(0.005)
Mother:	health change (0-10)	-0.001	-0.002	0.001
		(0.004)	(0.005)	(0.006)
Adjusted R^2		0.02	0.01	0.02
Number of HH		905	550	508
Obs.		5230	2738	2492
Delay:			daughters	sons
Child:	female=1	-0.046		
		(0.016)**		
Father:	health shock	-0.014	-0.033	0.009
		(0.022)	(0.030)	(0.032)
Mother:	health shock	0.000	-0.016	0.027
		(0.025)	(0.033)	(0.037)
Adjusted R^2		0.02	0.02	0.03
Number of HH		937	568	532
Obs.		6671	3473	3198

Note: Fixed effect is for households. Robust standard errors in parentheses. * significant at 5%; ** significant at 1%. Controls include parents' age, race, education, assets, and baseline health.

Table 3.7: **Highest Grade Completed and Delay: Changes in Parental Health: Fixed Effects — Includes Child's Age-Parental Health Decline Interactions**

		(1)	(2)	(3)
Highest grade	completed:		daughters	sons
Child:	female=1	0.194		
		(0.127)		
Father:	health shock	0.581	0.445	0.468
		(0.148)**	(0.222)*	(0.187)*
	age 12-15*shock	-0.843	-0.886	-0.317
		(0.131)**	(0.259)**	(0.117)**
	age 16-19*shock	-0.162	-0.110	-0.006
		(0.081)*	(0.117)	(0.103)
Mother:	health shock	0.228	0.190	-0.094
		(0.162)	(0.230)	(0.223)
	age 12-15*shock	-1.095	-1.311	-0.424
		(0.212)**	(0.337)**	(0.192)*
	age 16-19*shock	-0.031	-0.208	0.305
		(0.100)	(0.147)	(0.113)**
Adjusted R^2		0.33	0.31	0.44
Number of HH		1244	740	764
Obs.		7540	3739	3801
Delay:			daughters	sons
Child:	female=1	-0.038		
		(0.018)*		
Father;	health shock	-0.024	-0.048	0.000
		(0.024)	(0.033)	(0.035)
	age12-15*shock	-0.064	-0.046	-0.069
		(0.018)**	(0.031)	(0.025)**
	age16-19*shock	0.018	0.023	0.019
		(0.010)	(0.015)	(0.015)
(0.143)	(0.154)	(0.185)		
Mother:	health shock	-0.017	-0.025	0.004
		(0.025)	(0.035)	(0.037)
	age12-15*shock	-0.025	-0.008	-0.024
		(0.012)*	(0.013)	(0.015)
	age16-19*shock	0.017	0.009	0.023
		(0.013)	(0.017)	(0.019)
Adjusted R^2		0.02	0.02	0.03
Number of HH		905	550	508
Obs.		5230	2738	2492

Note: Robust standard errors in parentheses. * significant at 5%, ** significant at 1%. Controls include parents' age, race, education, assets, and baseline health.

CHAPTER IV

Parental Health and Children's Labor Force Participation

4.1 Introduction

There is a recent and growing literature examining health as an asset within families. Both health, of its own importance, and its association with economic factors, such as labor market participation, education, earnings, and poverty have been studied extensively, particularly for individuals. Only recently has this substantial health literature branched into studying health and the economic impacts of poor health in the context of a family. Most of the attention has been recently focused on how family financial or health assets can impact children's human capital accumulation, specifically their individual health and education. Less attention has been paid to how family health may impact children over the long-term, specifically in terms of their eventual labor market participation.

This paper contributes to the growing literature on family health and economic impacts by documenting the existence and the size of the association between parental poor health and children's later employment status. We present motivation and evidence of a long-term association between poor parental health and children's labor market participation. Health within the family, family income and assets, and children's human capital accumulation are interrelated, through a number of possible, multi-directional pathways. Given the complicated nature of these relationships and the limitations of available data, it is a daunting task to disentangle these pathways and estimate them separately. Here, we focus on describing the observable, long-term association between parental health and children's labor force participation. We view documenting this association as a first step towards building a more complete picture of the dynamic relationship of health and labor market participation, within families.

To motivate an economic framework that links parental health and children's labor market participation, we discuss a model of time allocation and labor supply. Using Gronau (1977)'s model of time allocation which includes market work, leisure, and home production, we hypothesize that one of the main possible pathways is that poor parental health reduces family resources and therefore harms children's human capital accumulation, eventually manifesting in reduced adult labor supply. Though we cannot identify this human capital channel directly, we empirically document the long-term association of parental health and children's labor supply using two longitudinal data sets containing detailed information on parents' health and labor market information for their children.

The paper proceeds as follows: we next present a literature review in section 4.2 and place our work in this context. Section 4.3 discusses an adaptation of Gronau (1977)'s theory model of individual time-allocation and market labor supply, to include transfers between parents and children. Section 4.4 describes the two data sources we use to empirically evaluate the model's predictions. Section 4.5 presents our estimates of the labor supply effects of poor parental health ten years prior. Section 4.6 concludes.

4.2 Literature Review

There is an extensive and exhaustive body of work in each field of health, family and labor economics. Only recently are certain intersections of these topics being examined in the literature. This paper contributes to work in that intersection, particularly focusing on the connection between parents' health and children's labor supply decisions later as adults. We describe a long-term association between poor parental health and children's probability of working. We use a simple theory model involving individual time allocation and market labor supply to motivate a possible relationship between unhealthy parents and reduced labor supply for children as adults. We find empirical evidence of this long-term association in two panel datasets, the Panel Study of Income Dynamics (PSID) and the Health and Retirement Study (HRS). Results using both data sources show a decline in children's labor supply ten years after their parents report being in poor health.

While we use an extension of Gronau (1977)'s model in this paper, the theoretical model most commonly used in the health literature is Grossman (n.d.)'s adaptation of Becker's human capital model into a theory of demand for health. Briefly, in Grossman's model, health has both consumption and investment aspects. Maintaining or improving one's health requires some financial and time inputs, for example medical care and time spent exercising, eating well, etc. Health is therefore intertwined with socioeconomic status, since those with more economic resources are in better positions to invest in their own health. James Smith has done extensive work in this area, researching the possible directions of influence relating health and economic status (Smith (1999), Smith (2007)). Health status has been recognized as an important component of human capital that influences labor market productivity, hence labor income.

Most of this health literature focuses on individual health and has only recently branched out to explore family member's health as an important factor in individual's decision making regarding both health and labor force status. Anne Case, Christina Paxson, and coauthors have focused on family health as an asset that impacts children's later economic outcomes: they find that health is a potential mechanism for lack of mobility across socio-economic states, in that children in poorer families have poorer health and lower investments in human capital, which are associated with lower labor market earnings (Case et al. (2005)). Later studies focus on children's health as the outcome of interest, driven primarily by differences in family income and socio-economic status (Case et al. (2008)).

Adverse health events, particularly health problems occurring at prime working ages, can have significant, long-term impacts on family member's economic behaviors due to the corresponding income loss. Despite such plausible spillover impacts from parents' health to child's labor outcomes, this issue has been under-explored in economics.

Recent studies have suggested that the family's economic network can be an important source of income among lower-income populations (Haider and McGarry (2005), Sloan et al. (2002)) and young adult populations (Schoeni (1997)) in the United States. Focusing on intergenerational relationships, this paper also attempts to address how important a role informal transfers play in the link between parents' health and children's labor market outcomes. The presence of parental health problems implies that both monetary and time transfers enter importantly in family members' choice sets. Therefore, consequent labor outcomes, particularly for children through adulthood, will vary depending on various aspects such as initial economic conditions, geographic proximity, social network availability and so on.

To begin to understand the mechanisms through which poor parental health affects children's subsequent labor force status, it is necessary to study possible pathways relating them. We assume that the relationship between parental health and children's labor market participation is mutli-faceted and complex, therefore our discussion of pathways is more descriptive than precise. We are not currently able to separately identify the different pathways, but as research in this area progresses, we anticipate being better able to trace out these separate linkages. Figure 4.1 illustrates a few of these possible pathways. Specifically, poor parental health is seen as depressing family income, which can in turn lower both children's educational attainment and health investments. Both reduced human capital accumulation through education and health are associated with lower expected earnings as adults. If an individual can choose between labor market and home production, as in the Gronau model, lower expected earnings may increase the marginal return to time spent in home production, relative to market work, therefore reducing children's labor market supply. Other pathways include time spent in care-taking for the ill parent. Such a shift in the child's allocation of time may negatively impact their educational attainment and individual health as well. Currie (2009) provides an overview of the empirical literature on family health and children's outcomes. Ferris et al. (2009) use a similar sample of children in the HRS to find both delays in education and lower long-term educational attainment for children with ill parents. Children who have accumulated less human capital than those with healthier parents may encounter barriers to labor force participation. Regardless of their desire for market work, employment opportunities for these children with less human capital, who are more likely to be from lower-income families, may not be available because of, for example, barriers to entry due to search costs. Their observed probability of working is lower if children are in lower-income families.

4.3 Theoretical Framework: Health Implications in the Labor Market

The impact of unhealthy parents on their child's labor supply in adulthood can be theoretically ambiguous. In this section, we use an extension of Gronau (1977)'s model of home and market production to describe one possible pathway linking poor parental health and children's labor market participation. This pathway links poor parental health to reduced transfers to children, which are associated with lower human capital accumulation and lower expected wages for the child. The reduction in wage changes the relative marginal return to time spent in the labor market versus home production, here associated with reduced labor market supply.

Unhealthy parents reduce their labor supply in their prime working ages, relative to similar but healthier parents, resulting in an adverse income shock for the family, in addition to medical costs. This decrease in family income may induce children to increase their labor supply in order to compensate towards a certain level of consumption.

On the other hand, poor parental health may additionally lead to decreased human capital accumulation for the child. Such children may accumulate less education and fewer investments in their own health, due to reduced family income, than would similar children with healthier parents. With reduced education and health, controlling for other factors, we would expect a lower market wage for the child of relatively unhealthy parents. Facing a lower wage, the adult child may reduce her own labor supply if the substitution effect for hours worked versus leisure time dominates the income effect of her lower wage. If, in addition, the child needs to provide care-giving for her unhealthy parents, this could result in a further reduction in her time spent on market work.

To understand these two competing mechanisms for labor supply, we provide an economic framework showing how parents' health status may impact an adult child's decision to engage in market work.

Individual's Allocation of Time

Gronau (1977) provides a theory on optimal time allocation among (*i*) market work, (*ii*) non-market work (such as home production), and (*iii*) consumption time (i.e. leisure). In this model, which we outline in this section, an individual maximizes the amount of a commodity that he consumes. Call this commodity "X", and assume that consumption of X provides utility. X is produced by a combination of goods and services (C) and consumption time, i.e. leisure (L):

$$X = X(C, L). \tag{4.1}$$

Define leisure as time spent converting C into X. The individual is interested in C and L *only* as inputs in producing X; C and L do not directly provide utility to the individual.

In this model, goods and services (C) can be obtained in two ways: by using either market-labor income or non-labor income to purchase C in the market, or by home production of C:

$$C = C_M + C_N. \tag{4.2}$$

Let C_M denote goods and services purchased in the market. Two types of income can be used to obtain C_M: labor income (wM) and non-labor income (V). C_N denotes goods and services produced by home production (i.e. non-market labor).

Labor income (wM) is obtained by time spent working in the market. Denote time spent on market labor as M. The market labor production function can be written as $f(M)$. Market productivity, $f'(\cdot)$, depends on demographic variables D, health status H, and schooling S, and is measured as the market wage, w:

$$f'(M) = F(\,D, H, S) = w. \tag{4.3}$$

Market productivity is constant and does not depend on total market working time.

Non-labor goods and services or money transfers (V) are also used, in addition to labor income (wM), to purchase C_M.

The individual's budget constraint, given his choice of M, is then

$$C_M = wM + V. \tag{4.4}$$

By denoting time spent on non-market labor as N, the non-market labor production function can be expressed as:

$$C_N = g(N). \tag{4.5}$$

Non-market labor productivity, $g'(\cdot)$, is a function of time spent on non-market labor as well as demographic variables and health:

$$g'(N) = G(\,N|D, H), \qquad \text{where} \;\; g'(\cdot) > 0 \;\; \text{and} \;\; g''(\cdot) = G'(\cdot) < 0. \tag{4.6}$$

Non-market labor productivity *decreases* as more time is spent in non-market labor.

We assume that schooling does not enter the non-market labor productivity equation.[1]

Total time ($\overline{T}$) is spent in three ways: on leisure L, non-market labor N, and market labor M. The time constraint, then, can be written as:

$$\overline{T} = L + N + M. \tag{4.7}$$

Figure 4.2 describes an individual's optimal choice between C and L in order to maximize X. The individual's optimal choice will depend on both his ability to convert goods and services (C) and consumption time (L) into the commodity X, and his budget and time constraints (equations (4.4) and (4.7)). The necessary conditions for an interior optimum are that non-market labor productivity, $g'(\cdot)$, equals the marginal rate of substitution between C and L, which also equals the shadow price of time. If the individual works in the market ($M > 0$), this also equals the wage, w. Both of these conditions, with and without market labor, are depicted in Figure 4.2.

We define a level of necessary commodity consumption: $\underline{X}$, as in Choi (2008). To achieve this level of X requires a positive amount of external resources, $V > 0$. Define $\underline{X} = X(V, (L_{max} = \overline{T}))$. If the individual chooses not to spend *any* time in either market work (M) or home production (N), in order to reach $\underline{X}$, she must posess at least V, as shown in Figure 4.2.

Individuals can vary in their ability to convert goods and services and leisure into X. Demographic variables (D), health status (H), and schooling (S) help determine how effective an individual is at converting goods and time into the commodity X. Those with better health and more schooling are better able to produce X than

[1] Michael (1973) suggests schooling increases non-market labor productivity. He investigates the partial effect of schooling on an individual's expenditure pattern. However, such non-market expenditure activity is still directly associated with market values. There are limitations on evaluating the impact of schooling on productivity for other non-market activities of relevance to health research, such as care-giving.

otherwise. An individual has the following production function for X:

$$X_i = X_i(C, L \mid D, H, S). \tag{4.8}$$

Individual A is better able to convert C into X_A and, in Figure 4.2, will choose point 'a' as her optimal choice. Compare this outcome to individual B who is relatively less able to convert C into X_B. He will choose point 'b' in order to maximize X_B. One possible difference between the two individuals is that individual A may have more schooling S than individual B, all else equal.

As shown in Figure 4.2, Individual A spends her total time available in the following manner: $\overline{Ol_a}$ is spent on leisure, $\overline{l_a m}$ on market labor and $\overline{m\overline{T}}$ on non-market labor (i.e. home production). Individual B splits time only between leisure, $\overline{Ol_b}$ and non-market labor $\overline{l_b\overline{T}}$. We will next explore the implications for both individuals' labor supply decisions of a decline in V due to poor parental health.

Intergenerational Transfer

If economic hardship complicates labor market participation decisions, parents can play a major role in mitigating that hardship, particularly when state or federal aid is insufficient. If the economic hardship is induced by health problems, then monetary transfers between family members, such as those from prime working age parents to their young adult children, may play a more significant role in children's labor supply decisions. This section considers economic hardship associated with unhealthy parents and faced by children, ten years later as adults. Choi (2008) presents an extension to Gronau (1977)'s model, adding intergenerational transfers. In the extended model, Choi hypothesizes that poor parental health reduces family incomes and therefore also reduces monetary transfers from parents to their young adult children. The main theoretical contribution in Choi (2008) is to introduce intergenerational economic linkages to individual time allocation behavior in a model with home production.

It is particularly important to understand how family resources, including both financial and time resources, are distributed between parents and young adult children. This is necessary in order to correctly characterize the labor market participation of adult children in light of parental health issues. For an individual in our extended model, non-labor goods and services or money transfers, V, are comprised of private transfers (V^P), e.g. from parents to young adult children, and governmental aid (V^G).

$$V = V^P + V^G \tag{4.9}$$

V^P measures how family income is redistributed from parents to young adult children. It will depend both on the child's resources as well as those of the parents. Given the outcome of an individual's maximization problem for the commodity good X, and her necessary level of commodity consumption, $\underline{X}$, an individual can be described as relatively well off if $X - \underline{X} > 0$. Choi (2008) terms this measure ($X - \underline{X}$), or "excess resources". In the context of a family, V^P is determined by (i) the child's own excess resources, and (ii) her parents' excess resources ($X^P - \underline{X}^P$):

$$V^P = V(X - \underline{X}, \quad X^P - \underline{X}^P). \tag{4.10}$$

For example, if an individual has negative excess resources, i.e., if she produces X less than her necessary consumption level, but her parents have positive excess resources, her parents can transfer part of their excess resources to her, mitigating her economic hardship.[2]

$$V^G = V(X - \underline{X}) \tag{4.11}$$

V^G depends on an individual's own excess resources. Government transfers can potentially play a significant role in the association between parents' health and young adult children's labor supply decisions by altering V^P. For example, if unhealthy parents also receive state or federal aid in the form of medical coverage, the excess resources of these parents are larger than without government assistance. Greater excess resources may allow these unhealthy parents to transfer more resources to their working age children than in the absence of government transfers. Of course, these unhealthy parents will not receive enough government aid to achieve excess resources equal to or approaching those of similar, healthier parents. In terms of excess resources, poor health is detrimental. However excess resources may be transfered between family members to improve welfare. Here we focus on the transfer from parents to young adult children, V^P.

Figure 4.3 shows the adult child's optimization problem for both healthy parents and those in poorer health. The differences between the two are that: (*i*) children with parents in poor health have lower non-labor resources, i.e. lower V^P, than otherwise similar children with healthier parents, and (*ii*) this decline in resources from the parents can negatively impact the child's expected earnings in the labor market, therefore lowering their wage. In this model, the decline in resources from parents is assumed to lead to less accumulation of human capital. On average, individuals with

[2]If both parents and children have negative excess resources, we might not observe any transfer. If both have positive excess resources, there might be transfers in both directions between parents and children, but the variance is less likely to be directly associated with economic hardship.

less schooling earn lower average wages than similar, more educated individuals.

As was the case in Figure 4.2, individual A spends some time in market work, while individual B does not. In Figure 4.3, if these individuals have unhealthy parents, then their new optimal choices would look like points a' and b' respectively. As V^P is lower for both individuals, because of reduced excess resources from parents and a lower expected wage due to less human capital accumulation in the form of schooling, both individuals now choose *not* to spend any time in market work, and only engage in home production and leisure. While individual B does not change his labor participation decision — both with and without unhealthy parents he chooses not to work in the market — individual A changes her labor supply decision. Due to the decline in excess resources and the decline in her wage, individual A's optimal choice now excludes market work. On average, across a population of young adult children with parents who may be healthy or unhealthy, according to this model, we expect lower labor force participation if children have unhealthy parents.

4.4 Data and Sample

To empirically test the model's prediction that poor parental health is associated with a lower labor force participation rate for young adult children, we utilize two data sources: the Panel Study of Income Dynamics (PSID) and the Health and Retirement Study (HRS). Both are nationally representative, longitudinal datasets that are primary sources for empirical studies in this literature, relating health and family economic outcomes. They have different strengths and weaknesses, which we will discuss in this section, but both have information allowing us to examine a potential relationship between parental health and children's labor force participation as young adults.

The Panel Study of Income Dynamics follows a sample of almost 9,000 families in the United States, focused on collecting economic, health, and social behavior information. The PSID provides a unique resource for annually tracking families. In 1968 the PSID started with two independent samples: a cross-sectional national sample (SRC) and a low-income sample (SEO). Our analysis sample includes individuals from both the SRC and SEO samples in order to maximize our number of individual observations. To account for the over-representation of low-income families we utilize the PSID sample weights, intended to allow users to combine the two samples and also account for differential mortality and attrition, in order to calculate statistics that are generally representative (Fitzgerald et al. (1998)). We use annual surveys beginning in 1986 through 1996 because the earliest health measurement for all individuals was first collected in 1986. Beginning in 1997 the PSID substantially reduced the size of the lower income sample (SEO), so we end our panel in 1996. These two constraints, both health information and a reasonable sample size, constrain us to use a decade as the longest time frame with the PSID. In our analysis sample we use parent's health as reported in 1986 and their child's employment status later in 1996. We identify intergenerational relationships in the PSID by using the family map file, which allows us to track young adult children even after they have moved out of their parents' house.

The Health and Retirement Study is focused on retirement-aged individuals and their spouses, collecting expansive information on health and financial information. The HRS also has information on respondents' children, including education and labor force status as young adults. Further data includes transfers between parents and children. Of specific interest to this study: services (e.g. caring for grandchildren) and financial transfers. HRS interviews began in 1992 and respondents are re-interviewed every other year. Respondents in the initial sample were between the ages of 51 and

61. We use information from 1992 to identify children of these initial respondents and their spouses, and we then rely on the longitudinal linking codes in the child-level HRS tracker file to follow these children to their parents' interviews ten years later, in 2002.

Our analysis samples from the PSID and HRS both span ten years, but begin at different baseline years: 1986 (PSID) and 1992 (HRS). Fundamental features of the surveys prevent creation of a sample that overlaps for 10 years. Sample size in the PSID is much smaller than the HRS even prior to 1997, but declines dramatically afterwards with the reduction in the SEO sample in 1997. Health information for the PSID only begins in 1986, leaving us with the PSID sample from 1986 - 1996. Currie (2009) asserts that results relying *only* on the PSID may be questionable because of the small sample sizes. Smith (2007) contains a discussion of the advantages of using the PSID to estimate the impact of socio-economic status on health over all possible ages, not simply focused on retirement-aged individuals, as in the widely used HRS. Smith (1999) uses both the PSID and HRS to explore the relationship between health and economic status.

The HRS began only in 1992, and while a four year overlap between data sources may be illustrative as we can use the PSID through 1996, we are exploring the longer-term relationship between parental health and children's labor supply. While ideally we could be able to follow both samples over an identical time period, this staggering over time highlights a particular form of governmental aid, targeted at increasing labor force participation, that impacts *only* the HRS sample. In 1996 welfare reform in the United States had a dramatic impact on labor force participation among lower-income families, particularly for younger women with children; see e.g. Blank (2002). The introduction of welfare reform in 1996 plausibly explains differences we find in estimates of labor supply between the PSID and HRS (see results in the next section).

Because our PSID analysis sample ends in 1996, due to sample size concerns, we do not expect that those individuals were affected by welfare reform[3] Our HRS analysis sample, on the other hand, because it contains information from 1992 to 2002 may have been affected by welfare reform. Because welfare reform was intended to increase labor force participation, particularly among eligible women, it may be an important factor for children's labor supply decisions after 1996, particularly for those welfare-eligible daughters whose parents were in poor health in 1992.

Our unit of observation is the young adult child. To construct samples as similar as possible from both the PSID and HRS, we focus on a homogenous group of young adult children: (*i*) parents are married and reside together in the baseline year, (*ii*) the child is the biological child of both parents, and (*iii*) young adult children are between 18 to 29 years old in the baseline year. Further, because the HRS interviews parents and not their children directly, in order to follow the same child 10 years out, we further restrict the sample to (*iv*) those children with at least one parent living in 2002. Similarly, for the PSID, even though children are interviewed independently, we restrict our sample to those with at least one living parent in 1996.

Table 4.1 presents summary statistics for key variables in our analysis. The PSID sample has 1,202 children who fit the sample criteria listed above. Of those children, 595 are sons and 607 are daughters. Our analysis sample for the HRS, again fitting the criteria listed above, has 10,798 children who were 18-29 years old in 1992: 5,490 sons and 5,308 daughters.

Average ages for children, both sons and daughters, are higher in the HRS sample than in the PSID sample, because HRS parents are near retirement age and are

[3] We check for the impact of welfare reform on a subsample in the PSID: the SRC sample, between 1992 and 2002. The proportion of sons and daughters for both the SRC sample and the HRS analysis sample are graphed in the results section, and both show a significant increase in the probability of working for daughters post-1996.

therefore older than PSID parents. The average age for children in the PSID sample is 24 while the HRS is 25. Figure 4.4 shows the distribution across ages 18 to 29 in both samples; the age distribution in the PSID sample is fairly uniform. However, in the HRS the age distribution is strictly increasing from age 18 to 28.[4] The average age of mothers in the PSID sample is 51, and in the HRS is 52. For fathers, in the PSID sample, their average age is 54 but in the HRS sample, their average age is 56.

In order to quantify parents' health, we rely on their self-reports. In both the PSID and HRS, survey respondents are asked to report on their general health status by rating their own health on a scale of one to five, where one corresponds to a report of "excellent" health, then "very good", "good", "fair", and finally five indicates "poor" health — the lowest category. In this paper, we categorize parents as "unhealthy", or refer to them as "in poor health", if they report either "fair" or "poor" health: the bottom two categories for general health status. In the HRS sample, 33% of children have at least one unhealthy parent in the baseline year: 1992. Similarly, in the PSID sample, 33% of sons and 38% of daughters report at least one parent is unhealthy in 1986.

Other variables that we include as controls in the estimation results, presented in the next section, include mother's age in the baseline year and indicators for race. We next include indicators for mother's education, family income and child's proximity to parents' home, all in the baseline year. Again, because mothers in the HRS sample are generally older than those in the PSID, a higher percentage have completed at least some college or more years of education. In the PSID, 22% of mothers have some higher education, relative to 33% of mothers in the HRS sample.

[4] We have explored resampling from the HRS in order to replicate the age distribution of the PSID sample, because the HRS has many more observations to work with. Results, presented in the next section, are not substantially different with the PSID-age-adjusted HRS sample than with the HRS sample described above.

Other factors that influence adult children's labor force participation include schooling and educational achievement, marital status, and the presence of children. Of interest to our theoretical section, extending the home production model to include intergenerational transfers, we have information on the proximity of children to their parents. In our sample, proximity takes on values of 0 or 1. If the child currently resides with his or her parents, or is in school, proximity is coded as 1. Proximity is also recorded as 1 if, in the PSID, the child resides in the same county as his or her parents, or in the HRS, if the child lives within 10 miles of his or her parents. In the HRS sample, just over 50% of children ages 18-29 have proximity = 1 in the baseline year, and ten years later, only 41% of children are living with or live within 10 miles of their parents. Note that in the HRS, daughters are more likely than sons to have at least one child themselves (i.e. grandchildren, from the perspective of the HRS parents). In fact, in 2002, 64% of daughters have at least one child, while only 53% of sons have children. Children are an important factor in labor force participation decisions, both for women and men, but the higher incidence of women with children in the HRS may help to explain differences in the association of labor supply and poor parental health, for sons versus daughters, particularly after welfare reform was implemented, in 1996.

Figure 4.5 presents trends in labor force participation, specifically the proportion that are working in the labor market, over time, for both the PSID and HRS analytic samples. In the PSID, individuals are asked a labor force status question, where possible answers include "working now", "looking for work", "student", "retired", etc. If the individual, in our sample, the child, answers "working now" we count them in the proportion that is working in Figure 4.5, whereas those children who answer "looking for work" are not counted as currently working. In the HRS, however, parents are asked about their children's employment status, and can answer that their child is either working full time (30 or more hours per week), part time (less than 30 hours) or not working. We included children, reported by their parent to be working either full or part time as part of the proportion working, in Figure 4.5.

Overall, young adult children with unhealthy parents are less likely to be working, at any age or year. As shown in Figure 4.5, in both samples, almost all of the sons are working, 80% to 95%, ten years later, however daughters are less likely to be employed. A majority of daughters work; about 75% in both samples, ten years after the baseline. But in both the PSID and HRS, daughters are less likely than sons to be working, regardless of parental health. Daughters' probability of working is primarily determined by marital status and children whereas sons' probability of working is not as influenced by the presence of children, but is sensitive to marital status. In the baseline years, the average child in the HRS sample is older than in the PSID. In the baseline year, both sons and daughters are less likely to be working in the PSID versus the HRS sample. This difference is likely driven by the average age difference, and because PSID children are younger, on average, they are also more likely to still be in school in the baseline year. Finally, daughters in the HRS with unhealthy parents appear to be somewhat unique in that their trend is increasing over time, towards convergence with daughters of healthy parents. This pattern is particularly striking, when compared to both daughters in the PSID sample and sons in the HRS. We present results, in the following section, indicating that the increase in employment probabilities for daughters corresponds to the time frame when welfare reform was introduced, in 1996.

4.5 Estimates of Labor Supply Effects

The labor supply model, incorporating excess resources, predicts that young adult children whose parents were unhealthy will then be less likely to spend time in market work. We use the PSID and HRS samples to empirically test this relationship. In the model, we link poor parental health both to less schooling, on average, and reduced transfers to children. In this paper we examine the long-term impact of poor parental health on children's labor market status as adults. In terms of employment status, in both the PSID and HRS samples, we find that young adult children with unhealthy parents are less likely to be working ten years later. Regarding unemployment, using only the PSID sample, because the HRS does not collect information on children's unemployment, we find that children with unhealthy parents are also more likely to be looking for work, if not already working. We begin to examine some initial evidence contributing to the long-term association between poor parental health and reduced labor market participation of children. Specifically we use both panel datasets to study initial evidence on some shorter term impacts, including the effect of welfare reform.

Figure 4.6 shows the observed differences in employment probabilities by sons and daughters in the PSID and HRS samples, who have healthy or unhealthy parents, between the baseline year and ten years later. Focusing only on the baseline year, in both the PSID and HRS, and for both sons and daughters, children with unhealthy parents are less likely to be working, both contemporaneously and ten years later. In our empirical analysis, we control for other observable characteristics related to family well-being and individual labor force decisions. This helps determine what proportion of these observed differences in working probability by parental health status, shown in Figure 4.5, can be explained by observable factors.

Table 4.2 presents estimates from the following reduced-form specification:

$$M_{b+10} = \alpha + \beta_1 H_b + \beta_2 D_b + \beta_3 D_{b+10} + \epsilon.$$

estimated as a logit regression, where M_{b+10} is an indicator for working in the labor market, or not, ten years after the baseline year. So for the PSID, $b + 10$ is 1996 and is 2002 in the HRS. H_b is an indicator for parental health in the baseline year, b, which is 1986 in the PSID and 1992 in the HRS. H_b takes on the value of 1 if at least one parent reports his or her general health to be either "fair" or "poor" in the baseline year. Additional demographic controls are included, some in the baseline year and some ten years later. D_b are demographic variables in the baseline year and include mother's age, race, education, family income, and proximity of the child to the parents' residence, in the baseline year. D_{b+10} adds additional controls in the same year as the outcome measure: indicator for working in the market, measured ten years after the baseline year. D_{b+10} includes the young adult child's marital status and completed education ten years after baseline. The coefficient of interest is β_1, measuring the association between poor parental health and adult children's labor force participation ten years later. Predictions based on the theoretical motivation presented earlier indicate that β_1 is expected to be negative, if the reduction in family resources and therefore child's human capital accumulation dominates other pathways.

Results in Table 4.2 suggest that there is a significant negative relationship between poor parental health when children are 18 to 29, and young adult children's labor force status ten years later. Estimates using the PSID sample are presented in the first four columns, separately by child's gender and for two sets of control variables. Results for the HRS sample are presented in the last four columns.

In the PSID sample, having at least one unhealthy parent in the baseline year (1986) is associated with a lower probability of working ten years later (1996) for both sons and daughters. In column (1) the estimate of β_1 for sons in the PSID is -1.144 and is statistically significant at the 1-percent level. A son's predicted probability of working in 1996 is 95.7% with healthy parents, while only 87.5% with unhealthy parents in 1986, controlling for differences in mother's age and race and evaluated at their means. Column (2) updates this specification with additional explanatory variables: mother's education, family income, and the son's geographic proximity to his parents, all in the baseline year. The estimate of β_1 is -1.035 and the predicted probability for working does not change: 95.6% for healthy parents and 88.5% for unhealthy parents. In column (3) the estimate of β_1 for daughters is -0.585 and is statistically significant at the 5-percent level. Daughters' predicted probability of working ten years later is 80.0% with healthy parents but only 69.1% with unhealthy parents, in the baseline year. In column (4), which adds additional controls, D_{b+10}, the results are quite similar for PSID daughters.

The HRS results are presented in columns (5) - (8) of Table 4.2. For sons, having at least one unhealthy parent in 1992 is associated with a lower working probability in 2002. The estimate for β_1 in column (5) is -0.541, and is statistically significant at the 1-percent level. Predicted probability of working, for sons with healthy parents, is 92.6% and with unhealthy parents: 88.0%, evaluated at the sample means. When evaluated separately by mother's race, for both white and non-white sons in the HRS, there are statistically significant differences between predicted probabilities of working for those with healthy compared to unhealthy parents. Column (6) adds additional control variables in 2002, reducing β_1 to -0.351, which is significant at the 5-percent level. The final two columns in Table 4.2 pertain to daughters in the HRS sample. While the sign on β_1 in both columns (7) and (8) is negative, the estimates for daughters are not statistically different from zero. We will show evidence later, using the HRS panel — interviews every other year between 1992 and 2002, not just the longest gap — that daughters in the HRS sample with unhealthy parents are *more* likely to work after 1996, relative to daughters with healthier parents. This is particularly noticeable for daughters with children.

Using the PSID sample, we can also explore different labor force states, including unemployment as well as employment in the labor market. Information on unemployment for children is not available in the HRS. Table 4.3 summarizes results for the PSID from a multinomial logit model for labor force status: working, looking for work, and not in the labor force. The multinomial logit coefficients in Table 4.3, columns (1) and (2), indicate that sons with unhealthy fathers are less likely to be employed ten years later, as was the case in Table 4.2, though for either parent being in poor health. Results for daughters are no longer statistically significant once the indicator for at least one unhealthy parent is decomposed into mother's and father's poor health, as shown in columns (3) and (4). However, if the daughters had unhealthy mothers in 1986 they were more likely to be unemployed and therefore looking for work ten years later, in 1996. Mother's and father's poor health does not have a statistically significant association with unemployment status for sons, as shown in columns (5) and (6). Predicted probabilities for both working and looking for work are listed in the middle of the table, based on sample means, and combinations of indicators for mother's and father's health. For sons, if both parents reported being in better health in 1986, their probability of working in 1996 is 97.0%, controlling for mother's age, race, education, family income, and proximity to parents in 1986. If both parents report poorer health, the probability for sons to be working in 1996 is 88.0%. Similarly, for daughters, their predicted probability of working in 1996 is 82.7% with healthy parents, and 2.2% with unhealthy parents in 1986. Differences in predicted probabilities of unemployment in 1996 are greater for those with unhealthy versus healthy parents. For sons, with healthy parents, their predicted probability of looking for work in 1996 is 1.8%, whereas if both parents report being in poorer health, that predicted probability is higher, at 5.4%. This difference is more pronounced for daughters: their predicted probability of looking for work is only 0.9% if both parents are relatively healthy in 1986. That predicted probability increases to 6.3% if both parents report being in poorer health in 1986.

4.5.1 Welfare Reform

To evaluate the results for daughters in the HRS sample in Table 4.2, we use six waves of HRS interviews, covering 1992 to 2002 and present results for both sons and daughters in Table 4.4. The specifications are pooled logit regressions; the dependent variable is an indicator for whether or not the child is working in that wave, as reported by the parents. Similar to results in Table 4.2, the first two columns of Table 4.4 show logit coefficients for sons and daughters whose parents reported in 1992 that at least one parent was unhealthy (first row) are less likely to be working throughout the panel. Columns 3 and 4 separate daughters into two groups: those with a high school education or less, and those with at least one year of college. The second row of Table 4.4 shows logit coefficients for the indicator variable for welfare reform, i.e. equals one for years 1998, 2000, and 2002, and for both sons and daughters (overall) they are positive, indicating that in the later years of the panel, children are more likely to be working. This is consistent with higher employment rates as young adults move into the beginning of their prime working years. In the HRS sample, the young adult children are aged 24 - 35 in 1998. The third row shows logit coefficient estimates for unhealthy parents interacted with an indicator variable for welfare reform. Fitting the welfare reform story, sons have a negative coefficient for this interaction while daughters have a positive relationship, implying that those daughters with unhealthy parents are more likely to be working after the implementation of welfare reform than are similar daughters with healthy parents.

As mentioned earlier, welfare reform was targeted primarily at low-income women and designed to increase their employment rate. Blank (2002)'s survey of the literature on welfare reform asserts that "These changes should have greatly increased the work incentives for low-wage single mothers with children." (p. 1108). Indeed, logit coefficients in Table 4.4, second row, show a more pronounced effect for daughters with lower educational attainment. For daughters with a high school education or less, the logit coefficient for the welfare reform indicator is both positive and large, relative to the coefficient for daughters with some college or greater, which is statistically indistinct from zero. Controlling for other observable characteristics listed earlier, such as mother's age, race, education, family income in 1992, daughters with less education are more likely to be working after 1996 than are daughters with more education, consistent with expectations for the implementation of welfare reform, since lower educational attainment is also associated with lower incomes.

Table 4.4 indicates that HRS daughters with unhealthy parents in 1992 were much more likely to be working in the years after 1996 (the pooled logit coefficient for column 2, row 3 is 0.339), than prior and relative to daughters with healthier parents. This pattern is distinct from HRS sons, whom were less likely to be working after 1996, if their parents reported being unhealthy in 1992: that logit coefficient is −0.198, in column 1, row 3. Translated into predicted probabilities of working, for children with healthy versus unhealthy parents, and using sample means for other control variables, Table 4.4 shows that sons have higher rates of working than daughters, overall. Sons with healthy parents have a predicted probability of working of 89.8%, whereas with unhealthy parents that falls slightly to 88.5%. Daughters, on the other hand, have an overall lower probability of working than sons. For all daughters in the HRS analytic sample, those with healthy parents have a predicted probability of working of 76.7% while those with unhealthy parents have a lower probability of 70.7%. Separating daughters by educational attainment, we see that daughters with some college or more education are more likely to be working: 81.6% for those with healthy parents, and 79.0% for those with unhealthy parents. The gap associated with parental health is larger for daughters with less education: for those with high school degrees or less, 67.5% are predicted to be working if they have healthy parents, while only 61.6% for those with unhealthy parents — a gap that is twice as large as the college-educated daughters.

Finally, evidence from a PSID subsample that can continue past 1996 also shows an increase in the probability of working for daughters after 1996, but no observed difference for sons. The SRC sample is a cross-sectional national sample and its key drawback is simply a small sample size. Sample sizes for each year are listed below the horizontal axis. Similar information for the HRS sample was shown previously, in Figure 4.7, where there is an upward trend in the probability of working for HRS daughters after, and during, 1996, but not for sons.

4.6 Conclusion

This paper shows evidence from two longitudinal studies that there is a significant, long-term impact on children's labor force participation as young adults, if their parents were unhealthy ten years prior. Generally, for both sons and daughters, we observe lower labor force participation if their parents were previously unhealthy. The behavioral responses are different among daughter's employment status, as measured in the PSID and HRS. We argue that the difference between the two cohort samples is due to the introduction of welfare reform in 1996, which disproportionally incentivized lower-income women into the labor force. These results suggest it is necessary to examine further how health and family structure, educational attainment, marriage and public policy can shape such discrepancies in labor force participation among family members over time.

Figure 4.1: **Pathways Connecting Parental Health and Children's Labor Supply**

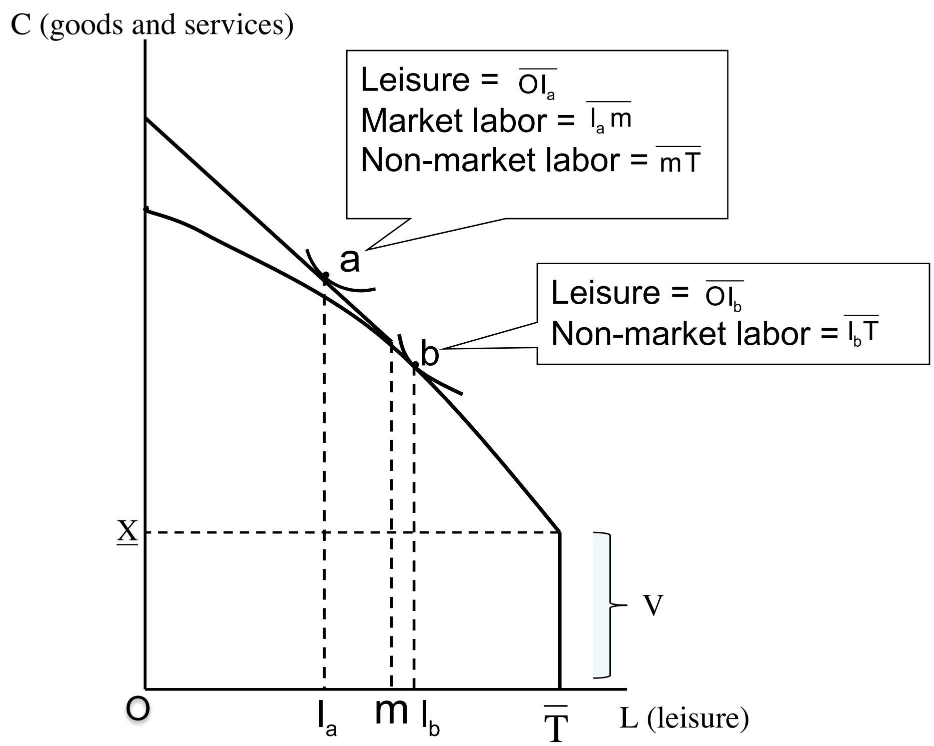


Figure 4.2: **Labor Supply Decision**

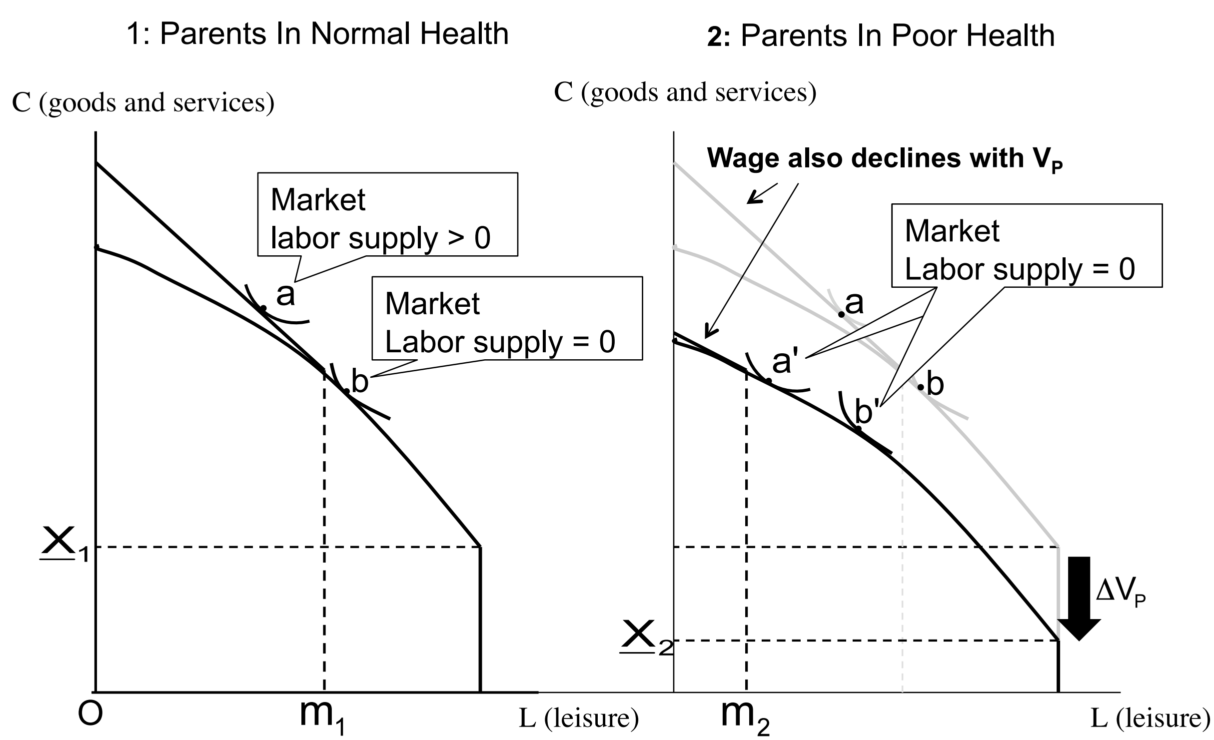
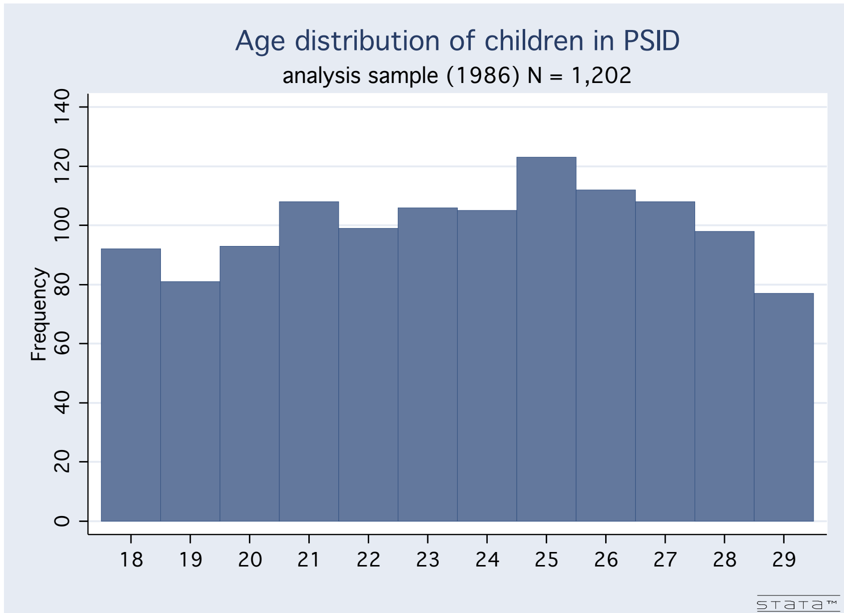


Figure 4.3: **Labor Supply Decision Associated with Parental Health**



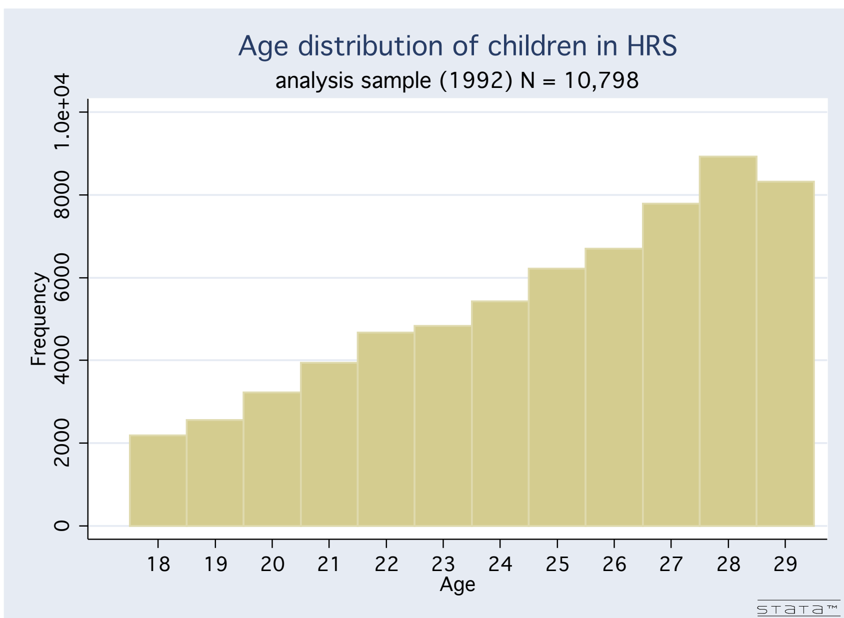


Figure 4.4: **Age Distributions in the PSID and HRS Analysis Samples**

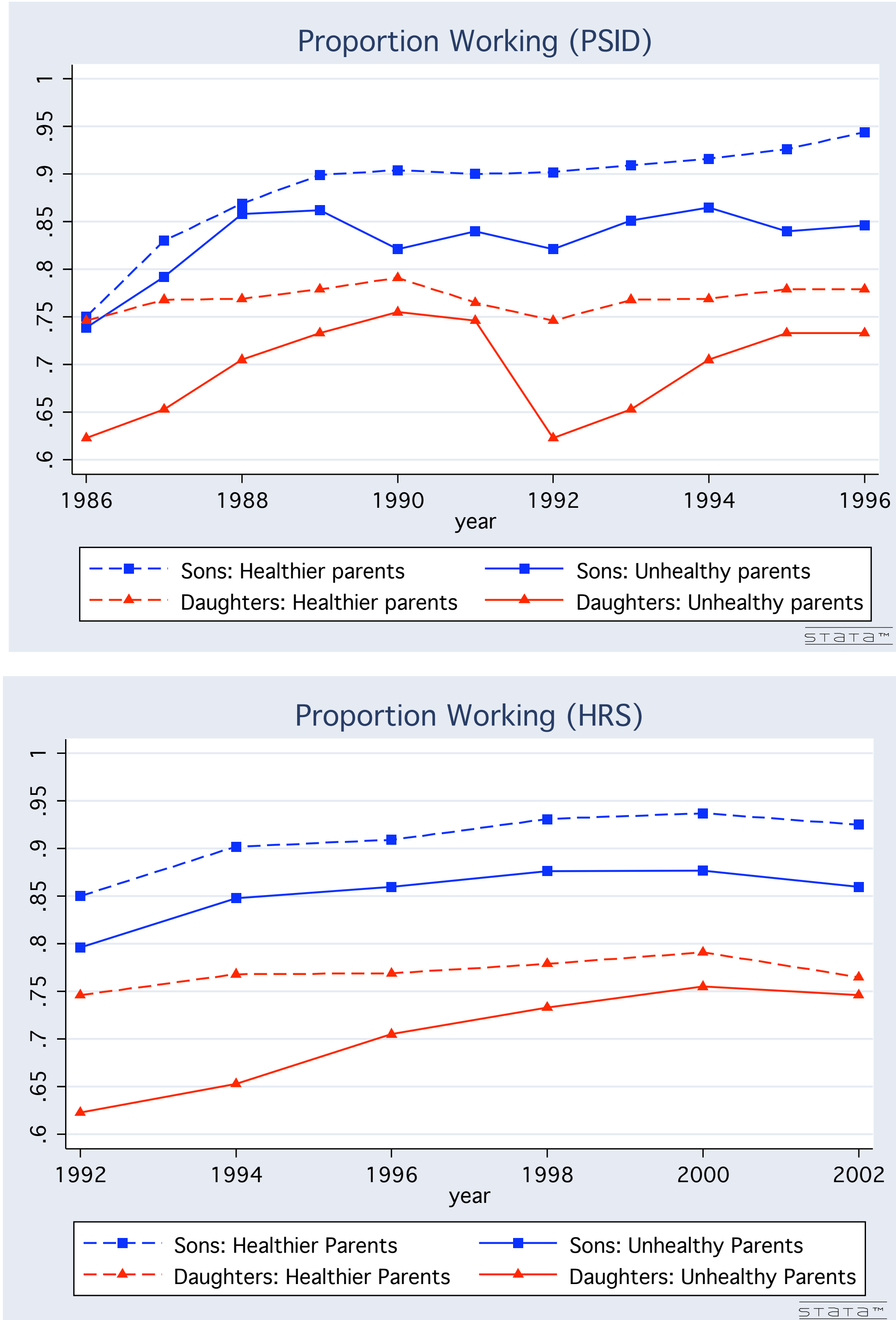


Figure 4.5: **Proportion Working, by Gender and Data Source**

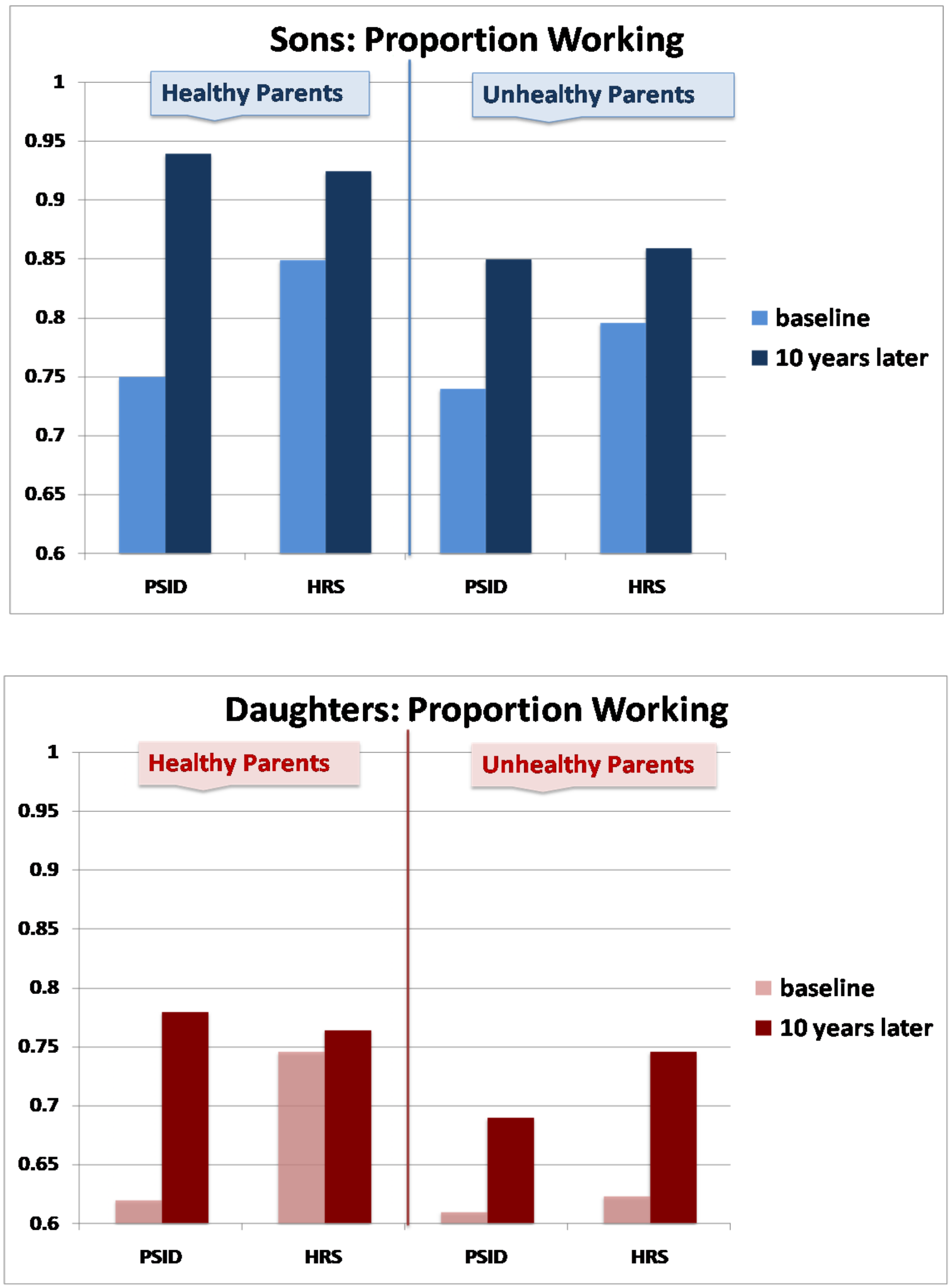
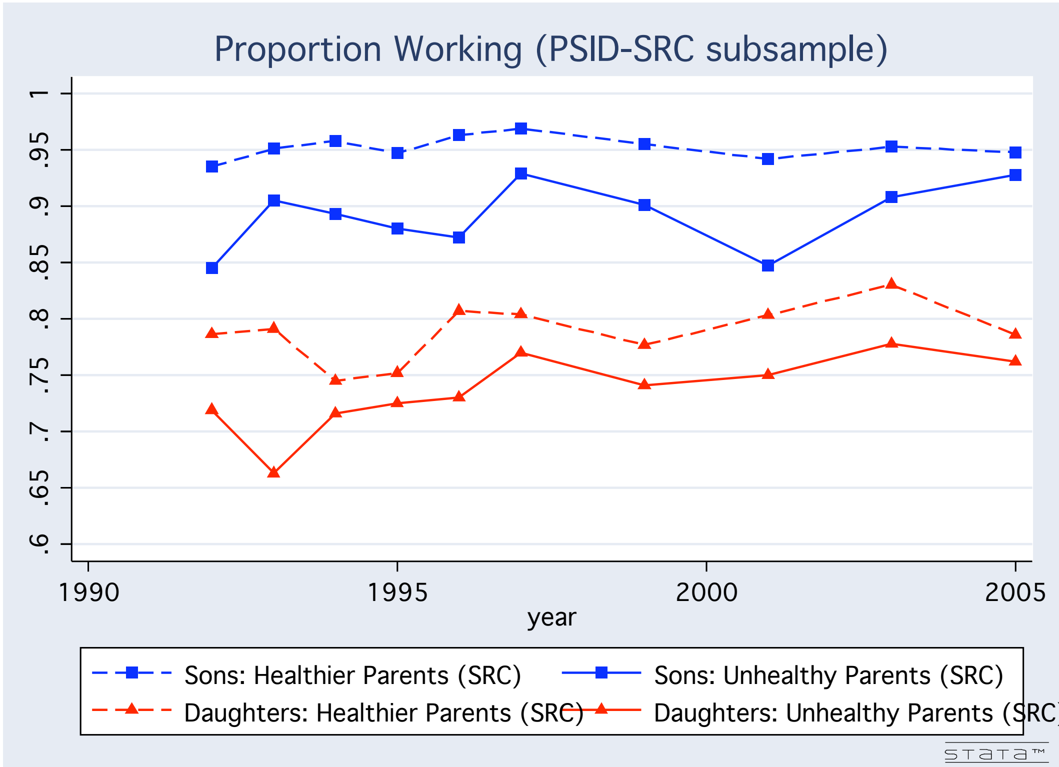


Figure 4.6: **Proportion Working, Baseline and Ten Years Later**



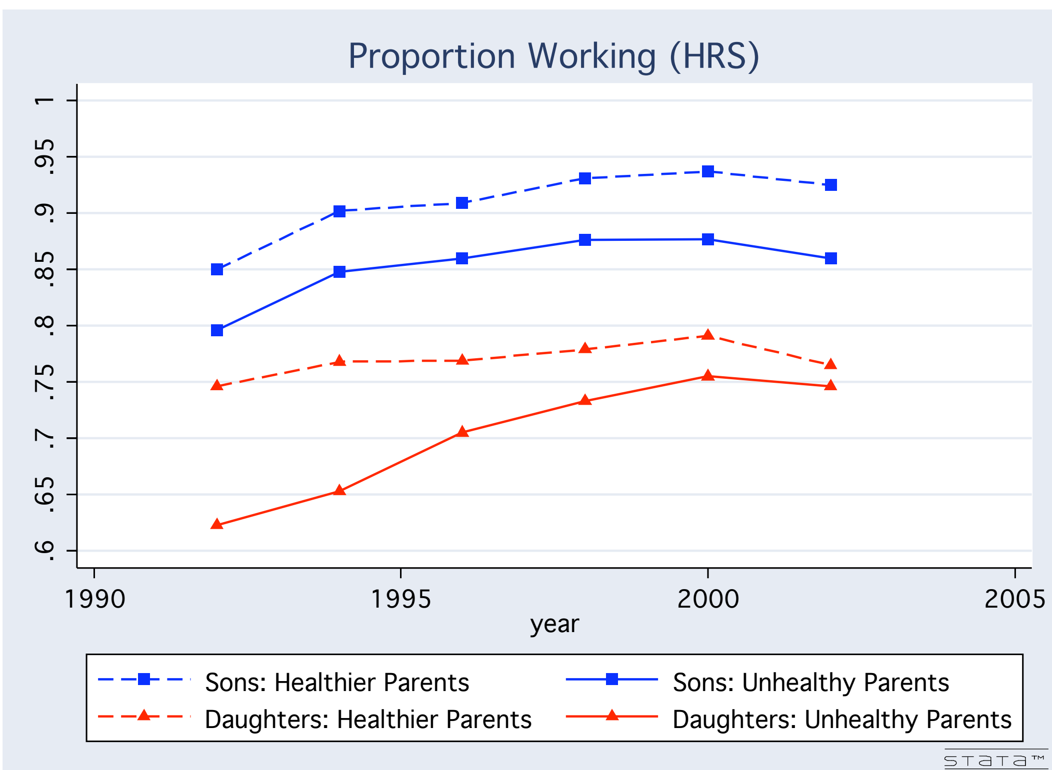


Figure 4.7: **Evidence of Welfare Reform in PSID Subsample and in HRS**

Table 4.1: **Summary Statistics**

	PSID		***HRS***	
Baseline year:	**Sons (N=595)**	**Daughters (N=607)**	**Sons (N=5,490)**	**Daughters (N=5,308)**
Child's age range: 18-29, sample mean	23	24	25	25
Mother's age, sample mean	51	51	52	52
Father's age, sample mean	54	55	56	56
At least one parent in poor health	33%	38%	34%	32%
Mother: higher education	24%	19%	34%	33%
Mother: white	73%	69%	64%	61%
Mother: African American	24%	29%	28%	29%
Mother: other	3%	2%	11%	13%
Family income, sample mean	$49,761	$49,274	$45, 913	$45, 324
Child: working	75%	64%	83%	71%
Child: in school	14%	12%	20%	21%
Child: any higher education	38%	41%	39%	46%
Child: married	31%	40%	35%	43%
Child: close proximity	69%	57%	57%	57%
10 years later:				
Child: working	91%	76%	91%	76%
Child: in school	1%	2%	3%	3%
Child: any higher education	44%	49%	49%	58%
Child: married	62%	66%	57%	60%
Child: close proximity	37%	33%	41%	42%

Note: Inclusion criteria for analysis sample: (i) parents are married and living together in the baseline year, (ii) parents and child are biologically related, and (iii) child is 18-29 years old in the baseline year. "Close proximity" is defined as follows: in the PSID, within the same zip code and in the HRS, within 10 miles. In the PSID, "Child: married" is an indicator for the spouse being in the family unity, and in the HRS, parents report on whether or not their child is married.

Table 4.2: **Association Between Parents' Health and Child's Subsequent Probability of Working**

	PSID				***HRS***			
	Baseline year = 1986 (SRC+SEO) Outcome: Working 1996				Baseline year = 1992 Outcome: Working 2002			
Coefficient:	**Sons (N=579)**		**Daughters (N=589)**		**Sons (N=3,258)**		**Daughters (N=3,141)**	
At Least One Unhealthy Parent	-1.144***	-1.035***	-0.585**	-0.593**	-0.541***	-0.351**	-0.122	-0.055
In Baseline Year	(0.37)	(0.36)	(0.24)	(0.25)	(0.134)	(0.143)	(0.101)	(0.109)
Predicted Probability								
Healthy Parents	95.7%	95.6%	80.0%	80.1%	92.6%	92.5%	76.7%	76.5%
Unhealthy Parents	87.5%	88.5%	69.1%	68.9%	88.0%	89.7%	74.5%	75.5%
Baseline year controls								
Mother's Age and Race	X	X	X	X	X	X	X	X
Mother's Education, Family Income, and Child's Proximity		X		X		X		X

Sources: PSID and HRS. Analysis samples include only children ages 18-29 in the baseline year.
Note: Parents are defined as "unhealthy" if at least one parent reports being in "fair" or "poor" health in the baseline year. Coefficient estimates are from logit specifications, with an indicator for the child's working status. "Child's proximity" is an indicator; in the PSID it equals one if the child lives in the same zip code as his or her parents in the PSID, and in the HRS, if the child lives within 10 miles.

Table 4.3: **Association Between Parents' Health and Child's Subsequent Labor Force Status — Multinomial Regression, Reference Outcome: Not in the Labor Force**

	PSID							
	Baseline year = 1986 (SRC+SEO)							
Outcomes:	**Working 1996**				**Looking for Work 1996**			
Coefficients:	**Sons** (N=577)		**Daughters** (N=586)		**Sons** (N=577)		**Daughters** (N=586)	
Mother in poorer health	-0.503	-0.536	-0.496	-0.462	-0.311	-0.222	1.055*	1.210**
	(0.57)	(0.61)	(0.34)	(0.34)	(0.83)	(0.80)	(0.55)	(0.54)
Father in poorer health	-1.378**	-1.220**	-0.413	-0.479	-0.407	-0.319	0.042	0.054
	(0.63)	(0.60)	(0.28)	(0.30)	(0.91)	(0.87)	(0.61)	(0.72)
Predicted Probability:								
Mother and Father in good health	95.7%	97.0%	80.8%	82.7%	2.4%	1.8%	1.4%	0.9%
Mother in good but Father in poor health	87.5%	91.9%	73.5%	74.7%	5.8%	4.1%	1.9%	1.4%
Mother in poor but Father in good health	94.1%	95.5%	69.3%	72.8%	2.9%	2.4%	5.5%	4.4%
Mother and Father in poor health	82.8%	88.0%	59.8%	62.2%	6.7%	5.4%	7.4%	6.3%
Baseline year controls:								
Mother's Age and Race	X	X	X	X	X	X	X	X
Mother's Education, Family Income, and Child's Proximity		X		X		X		X

Source: PSID analysis sample; includes only children ages 18-29 in the baseline year, and uses PSID weights for both SEO and SRC samples.
Note: Parents are defined as being in poorer health if they report either "fair" or "poor" self-reported health in 1986. Coefficient estimates are from multinomial logit specifications, with an indicator for the child's labor force status: not in the labor force, looking for work, or working. Predicted probabilities are evaluated at sample means.

Table 4.4: **HRS Probability of Working, Including Welfare Reform**

	Sons	**Daughters**		
			H.S. or Less	**Some College+**
	(1)	(2)	(3)	(4)
Unhealthy parents (1992)	-0.136*	-0.309***	-0.256***	-0.163*
	(0.076)	(0.066)	(0.092)	(0.093)
Welfare reform (year>1996)	0.508***	0.105**	0.302***	-0.061
	(0.067)	(0.047)	(0.078)	(0.060)
Unhealthy parents * welfare reform	-0.198*	0.339***	0.252**	0.303**
	(0.110)	(0.083)	(0.121)	(0.126)
Predicted probability:				
Healthy parents	89.8%	76.7%	67.5%	81.6%
Unhealthy parents	88.5%	70.7%	61.6%	79.0%
Num. of obs.	20,597	19,874	7,319	12,110
log likelihood	-7,124.985	-11,052.16	-4,663.021	-5,879.302

Note: dependent variable is an indicator for working. Pooled logit coefficients, similar to Table 4.2, but using the entire HRS analysis panel (eight waves of interviews) instead of only 1992 and 2002. Standard errors are clustered by household, incorporating siblings. "Welfare reform" = 0 for 1992, 1994, and 1996, and =1 for 1998, 2000, and 2002. Other control variables are: mother's age, race, education, family income and child's proximity, all in 1992. Columns 3 and 4 separate daughters by their education level in 2002: high school or less, versus at least one year of college completed. Predicted probabilities are for either healthy or unhealthy parents in 1992, and sample means for other control variables.

CHAPTER V

Conclusion

In chapter II, I examine the local labor market impacts of an environmental regulation: protection of the northern spotted owl under the Endangered Species Act. I use geographic data on the location and size of critical habitat areas set aside from logging to protect the spotted owl in the Pacific Northwest and northern California to identify the proportion of the observed decline in timber employment and earnings in the 1990s that can be linked to owl protection.

I find that approximately sixty percent of the 30,000 lost timber jobs in the region and a decline of 2 percent in earnings per worker can be attributed to protection of the spotted owl. These estimates indicate that the local labor market impacts, for the timber industry, were negative, as expected with a decline in labor demand for the timber industry, but not as large in retrospect, as some predictions had suggested.

Analyses of spillover effects, both geographic, for comparison counties in the region, and sectoral, as unemployed timber workers may have taken jobs in other industries within the same counties that have owl-protected areas yield mixed evidence. While employment changes in comparison counties and non-timber industries in treatment counties are not different from zero, earnings per worker in non-timber industries in treatment counties declined by 5 percent, over 1990 to 2000. Robustness checks include estimates of the impacts across non-timber industries, and across other regions of the U.S. and British Columbia. Taken together, these results indicate that Northern Spotted Owl protection plausibly led to a small loss of timber earnings per worker and employment in the Pacific Northwest, with larger declines for counties with larger areas of owl-protection.

In chapter III, co-authored with Robert F. Schoeni and Robert J. Willis, we investigate how parents' health is associated with children's human capital accumulation and educational attainment. Human capital theory predicts that children in families with fewer resources achieve lower levels of educational attainment. Having unhealthy parents, independent of financial resources, may therefore lead to lower educational attainment for children. Using data from the Health and Retirement Study, we find evidence that children with unhealthy parents attain less education than similar children with healthy parents. Controlling for family assets and other background characteristics, daughters are significantly less likely to complete as many years of education as sons if their mother experiences a decline in health. This is particularly striking for younger children – for ages 12-15, daughters and sons are expected to achieve less education if their father has a health decline, but for daughters that probability is 1.5 times as large if the mother experiences the health decline. One possible explanation for the gender differenceis caregiving for an ill parent. Overall, we empirically establish a negative association between changes in parents' health and the childs educational attainment.

In chapter IV, co-authored with HwaJung Choi, we describe the long-term association of poor parental health on children's labor force outcomes in adulthood. We hypothesize that poor parental health reduces family resources and harms children's human capital accumulation. These two factors have competing effects on children's labor supply as adults: lower family income and increased medical expenses for ill parents increases the incentive to work, while the reduction in human capital leads to lower wages, reducing the incentive to work. To describe this long-term association empirically we use two representative, longitudinal studies with detailed information on parents' health and children's labor force status: the Panel Study of Income Dynamics and the Health and Retirement Study. We show evidence of a long term association of poor parental health and children's reduced labor force participation. Young adults, ages 18 to 29, whose parents reported being in poor health were less likely to be working ten years later, compared to similar young adults with healthier parents.

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