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Research Article

The Labor Market Consequences of Family Illness

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Abstract

Background: This study examines the impact of mental illness on the labor market performance of family members of afflicted individuals. Numerous research projects have attempted to measure the impact of mental illness and related disorders on the ill individual, yet have traditionally neglected estimating potential costs accruing to family members of the ill.

Aims of the Study: Previous research estimating the impact of illness on the time allocation decisions of family caregivers has been limited in scope. I obtain estimates of the impact of mental illness on the probability of labor force participation and hours of work of all family members. The general analysis used in this study will pave the way for more accurate assessments of the costs of *all* types of illness and the estimates obtained will provide policy makers with a much more complete picture of the costs of mental illness.

Methods: The main empirical work in this study includes a probit estimation of labor force participation and a tobit regression of hours worked (including sample selection correction). The data sample, taken from the 1987 National Medical Expenditure Survey, is also partitioned by gender to clarify effects of family illness on labor supply for both females and males.

Results: Adult males are found to *increase* their probability of labor force participation in the presence of mental illness in the family (all else equal) when the mental illness is accompanied by a chronic physical illness. However, females are surprisingly found to have no significant impact on their probability of being a member of the labor market when a family member is afflicted with mental illness. On the other hand, hours of work are significantly *reduced* for both females and males when the mentally ill family member is afflicted with additional illnesses (physical and/or mental).

Discussion: Previous studies have traditionally not considered the effects of family illness on males because females are typically found to be the primary caregiver when a family member falls ill. The findings in this study indicate that men suffer reductions in their hours of work in an equivalent magnitude to females. Thus, males should *not* be ignored when estimating the opportunity costs of illness in families.

Implications for Health Policies: Current federal and state policies provide for some of the medical costs and replace some of the lost income of ill individuals, but generally do not support family members who are negatively affected by illness. This research provides evidence supporting the arguments of advocates for policy to ameliorate the financial burden borne by family members of the ill.

Implications for Future Research: The estimates obtained in this study show that women and men both need to be studied when determining the effects of family illness on labor supply, and should be studied separately to obtain clear results. Also, future research should include examining particular mental illnesses to see whether there is a higher cost of one over the other (e.g., schizophrenia versus major depression), as this may provide valuable information to policy makers. In addition, comparison of the costs of psychological disorders to chronic physical illnesses (such as cancer and heart disease) should be undertaken.

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Introduction

In economics, models of time allocation explain the determination of labor supply. These models incorporate household production functions that determine maximum consumption levels of leisure and other goods. A common application includes a health production function, where the output—the individual's health—is a determinant of labor supply. In this study, the health application is extended to explore how the health of family members can also influence an individual's supply of labor.

In particular, this study examines the impact of mental illness on the labor market performance of family members of afflicted individuals. Mental illness is an appropriate illness to study in this context because it is highly prevalent in the United States. Diagnosable mental disorders affect about 30% of the US non-institutionalized population in any given year and almost 50% over the lifespan.[1] Further, because the family is a major support and caregiver for persons with severe and persistent mental illness,[2] the implications of this research are of particular importance to policy makers.

The purpose of cost-of-illness studies is to formulate a well defined set of estimates of the impact of disease.[3,4] Numerous research projects have attempted to measure the impact of mental illness and related disorders (e.g., alcoholism and drug abuse) on the afflicted individual.[5–10] Yet cost-of-illness studies have traditionally neglected estimating potential costs accruing to family members of the ill.[11] However, a complete summary of the negative consequences of illness must also include secondary effects. Only a few studies of general health status or illnesses other than mental

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illness have analyzed the effect of health on family labor supply decisions. These have generally considered the labor supply response of a wife to an illness of her husband; the labor supply response of a daughter to a disabled, elderly parent; or the labor supply response of a mother to a chronic illness of her child.[12–17]

Previous research estimating the impact of illness on the time allocation decisions of family caregivers has been limited in scope in several ways. First, largely due to data pitfalls, many studies limit their focus to specific populations of both caregivers and care receivers (for example, the effects on married women with elderly parents). Similarly, nearly all the studies consider just one family member (e.g., daughter, wife) to be the only potential caregiver, rather than allowing the possibility of an impact on the time allocation decisions of *all* family members. Second, the results obtained from most of these studies likely suffer from selection bias because the samples include only caregivers, persons who have already chosen to take on the caregiving responsibility. If the decision to provide care is correlated with an individual's labor supply (as we might expect), then estimates obtained from using such a sample will be biased. Third, data sources from local surveys have been used so that the results obtained cannot be generally applied for policy analysis.[2] Aggregate economic costs resulting from disability for the United States have also been estimated but these studies do not provide family-level impacts.[18,2]

Unlike prior studies, the analysis reported in this study is general. (i) *Any* family member may need care due to illness or disability. (ii) Because the labor supply choices of *all* family members may be affected by an illness in the family, even if there is a primary caregiver, the model allows *each* family member to adjust her or his labor market time. The theoretical model, a time allocation model, is general. With it I derive hypotheses describing the impact of a serious illness of one family member on the labor supply of other family members. The empirical analysis focuses on the impact of a mental illness in the family.

It is not clear whether or not reductions in labor market time are directly due to the individual *providing care* for the ill family member. It is possible that those who have a mentally ill family member will have an increased amount of stress and perhaps suffer from physical illnesses so that time *may* be taken away from work to deal with these indirect effects of the illness, not to specifically provide caregiving time. However, the focus of this study is to estimate foregone earnings due to the illness in the family, whether the lost hours of work are due to providing care to the ill family member or to obtain services for herself or himself. I obtain estimates of the impact of mental illness on the probability of labor force participation and hours of work of family members.

The empirical analysis uses data from the 1987 National Medical Expenditure Survey (NMES). Sociodemographic, labor force, income and health data are available in this nationally representative sample, and family members are linked by a common identifier. The use of the NMES data, along with careful attention to econometric issues such as selectivity, improves upon the current body of caregiving literature. Estimates are provided to quantify the opportunity cost of the illness to the family in terms of foregone earnings. The general analysis used in this study will pave the way for more accurate assessments of the costs of *all* types of illness and the estimates obtained will provide policy makers with a much more complete picture of the costs of mental illness.

The remainder of this study is presented in four sections. The following section develops the theoretical model and derives the hypotheses to be empirically tested. Next a description of the data source and layout of the empirical model is given. Estimates from each of the models are provided and discussed in the next section. This study concludes by summarizing the important findings and providing direction for future research.

Theoretical Model

When modeling labor supply in the context of the household, time allocation models are appropriate. Becker's seminal paper furthering the theory of time allocation[19] introduced a revised theory of choice, placing relative marginal importance on both foregone earnings and time in home production. In his model, Becker identifies consumption goods purchased by a household as either earnings-intensive or time-intensive commodities. This labeling enables us to anticipate a change in the mix of these commodities when, for instance, an individual's wage rises. Such an event would bring about a change in the relative prices of earnings-intensive versus time-intensive goods. Thus, we can hypothesize that a wage increase will generate a shift away from time-intensive and toward earnings-intensive goods, resulting in a decrease in the amount of time needed for consumption, thereby leaving more time to be spent at work.[20]

The time allocation model's 'building blocks' are the utility and household production functions.[21] These production functions estimate the time needed to transform market purchases into consumption goods. Each individual compares their productivity in the home with their productivity in the labor market to determine their optimal allocation of time between home and market work. With the goal being maximization of the family's utility, individuals with relatively low wages may find that their time is better spent performing duties in the household, producing consumption goods from time-intensive commodities. Likewise, we would expect those with relatively higher wages to spend more time in the labor market, using their wages to purchase earnings-intensive commodities. A change in either an individual's market wage or their productivity in the home brings about a change in the relative price of competing uses of the individual's time. The generated income and substitution effects alter the mix of home and market work to optimally allocate time in order to maximize the family's utility.[22]

Becker's standard time allocation model provides the framework for the empirical work in this study. The model is extended in the sense that a family member's health is a commodity produced in the home, with some combination of time-intensive and earnings-intensive goods. Given this, I am interested in how an individual's labor supply is affected in the presence of an ill family member. The individual's utility function is subject to the usual time and budget constraints, and maximization under these conditions determines optimal demand for consumption goods and work versus nonwork time.

A simple graphical illustration of optimal time allocation for an individual is shown in **Figure 1**, which has total consumption (*C*, in \$) on the vertical axis and total time endowment (*T*, in hours) on the horizontal axis. The individual's wage provides the slope of the budget line, and the tangency between the budget line and an isoquant from the individual's indifference mapping (which occurs on IC_1) determines the optimal non-work hours ($0L_1$). The household production function depicts the individual's ability to produce services in the home (versus purchasing them). The tangency between the budget line and the household production function provides the optimal hours spent working in the home (versus in the labor market), which is N_1T in **Figure 1**. Note that time in home production includes caregiving. Labor market time is found residually—the number of hours left over after leisure and home production hours are satisfied—and is L_1N_1 in **Figure 1**. Thus, the individual's total time endowment in **Figure 1** is optimally divided into $0L_1$ hours of leisure, L_1N_1 hours of market work, and N_1T hours of home production.

Algebraically, when an individual maximizes utility subject to their budget constraint, demand functions can be obtained for time allocation (i.e., hours of work, caregiving and other household production) and market goods. A major goal of this study is to examine the effect of illness on labor market time within this framework. Thus, it is the impact on the demand for labor market involvement in the presence of an ill family member that I wish to estimate.

Figure 2 demonstrates the impact of mental illness on the time allocation decisions of family members, other things equal. The presence of an ill family member (*familln*)

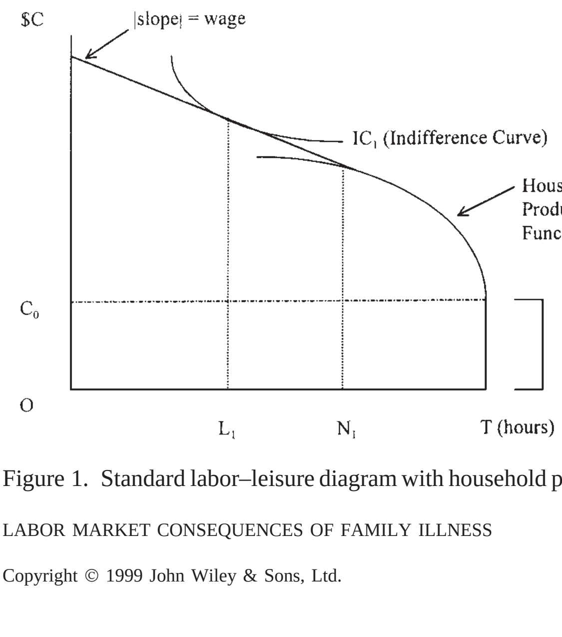
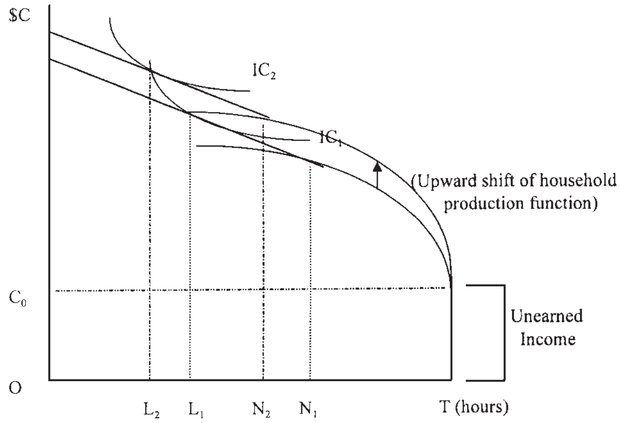


Figure 1. Standard labor–leisure diagram with household production



Note: Effect on labor market time (N_1L_1 to N_2L_2) is ambiguous; household production time increases from TN_1 to TN_2; leisure time decreases from OL_1 to OL_2.

Figure 2. Labor–leisure diagram for family members of the ill

raises the productivity of those engaging in household production. Consequently, the household production function rotates upward and to the right so that its slope is steeper at any level of time input. The result of this higher level of productivity is a greater amount of time devoted to household tasks (including caregiving), a reduction in leisure time, and an ambiguous effect on labor market time (*workhrs*). Thus, the sign of $(\partial(\text{workhrs})/\partial(\text{familln}))$ cannot be determined theoretically so the data will be relied on to provide us with the direction of this impact. However, if I assume that the increase in home production time is *exactly* offset by the decrease in leisure, then there is no effect on labor market time. This is my null hypothesis: $(\partial(\text{workhrs})/\partial(\text{familln})) = 0$. If $(\partial(\text{workhrs})/\partial(\text{familln}))$is estimated to be positive, we can conclude that the increase in home production os *not* fully offset by the decrease in leisure, so that *more* time is spent at work. Conversely, if $(\partial(\text{workhrs})/\partial(\text{familln})) < 0$, then we can conclude that the increase in home production is *more than* offset by the decline in leisure, leaving *less* time for labor market involvement.

If an ill family member needs care, this can be provided either directly by family members or indirectly by purchases made in the marketplace. How care is provided depends critically on the wages of the family members. An individual is more likely to be out of the labor force and at home caring for an ill family member if her or his market wage is less than their value of time in caregiving and other home production. Alternatively, caregivers are less likely to leave the labor market if they face a high opportunity cost of leaving. Family members with relatively high wages will remain in the labor force as long as their wage exceeds their value of time at home. Thus, optimal time allocation between labor market and caregiving time will vary as wages vary, highlighting the need to investigate $(\partial^2(\text{workhrs})/\partial(\text{wage})\partial(\text{familln}))$. The analysis presented here predicts that this second-partial derivative will be positive.

Finally, a change in unearned income (*Y*) will alter an individual's time allocation via a pure income effect.

Economic theory provides us with $(\partial(\text{workhrs})/\partial(Y)) < 0$. Including the impact of family illness, I hypothesize that $(\partial^2(\text{workhrs})/\partial(Y)\partial(\text{familln})) > 0$. That is, the presence of an ill family member will *increase the size of the reduction in hours of work* due to an increase in income.

In summary, I will investigate how labor supply varies with illness in the family and how this family illness, in conjunction with wage and income changes, affects optimal hours of work. The three hypotheses I wish to test are:

(i) $\left(\dfrac{\partial(\text{workhrs})}{\partial(\text{familln})}\right) = 0$

(ii) $\left(\dfrac{\partial^2(\text{workhrs})}{\partial(\text{wage})\partial(\text{familln})}\right) > 0$

(iii) $\left(\dfrac{\partial^2(\text{workhrs})}{\partial(Y)\partial(\text{familln})}\right) > 0.$

Data Description and Empirical Model

The empirical analysis in this paper is designed to test the hypotheses of the previous section. The impact of the presence of a mentally ill family member is examined for two labor market outcomes: labor force participation and number of hours worked. In this section, the data set used in the analysis is identified and described. Then, the estimating models are presented. First, a general two-equation approach is adopted and tested for selectivity bias. Next, I re-estimate the general model after partitioning the data by gender to further clarify the results. If there are opposing effects for women and men, this partitioning will provide clearer impacts of mental illness in the family on each group.

Data Description

The data are taken from the National Medical Expenditure Survey, 1987 Household Survey (NMES). There are just over 38 000 individuals in the sample, and person-level weights are available to extend the sample to represent the entire US civilian, noninstitutionalized population. The data is rich in its content of labor force, sociodemographic, time cost and human capital variables. In addition, NMES reports ICD (International Classification of Diseases) diagnostic codes from doctor visits, hospital stays, prescriptions, emergency room visits and outpatient treatments. NMES has been used extensively in health economics and health services research.[23,24] No other available data contains the combination of economic and health information needed for this research.*

For the purpose of this study, if an individual has been *diagnosed* with an organic psychotic condition, schizophrenic disorder, affective psychosis or other mental illness, they are classified as mentally ill. (Still others complain of being ‘nervous’, ‘down’ or ‘unhappy’ at some time during the month prior to the survey but are not necessarily *chronically* mentally ill and therefore are not labeled as such in this study.) Those with a chronic illness are most likely to be in need of caregiving time from family members and therefore have an impact on family members’ time allocation decisions.†

The empirical analysis is performed only on individuals of working age (those 18 to 64 years old) who are neither chronically ill, developmentally disabled nor mentally ill because I am interested in estimating the labor force and hours decisions for adults who are not chronically ill. In addition, because I wish to estimate the impact of an ill individual on labor supply decisions of family members, individuals who are single-member families are excluded. Dropping individuals in the sample who do not fit the desired working population leaves 9111 observations. **Table 1** presents descriptive statistics for this subsample.

Probit Analysis

The first analysis is a Probit estimation with labor force participation (LFP) as the dependent variable. The explanatory variables included are those that have traditionally been found to have an effect on LFP, with the addition of dummy variables indicating presence (or not) of a mentally ill family member (MIinFAM) or some other type of ill family member (OIinFAM). Of primary interest is the sign and magnitude of the marginal effect of MIinFAM (and interaction terms) since they indicate the impact of having a mentally ill family member on labor force participation, everything else held constant. The Probit equation is defined as follows:

$$\text{LFP}_i = \alpha_0 + \beta_1(\text{AGE})_i + \beta_2(\text{AGESQ})_i + \beta_3(\text{EXPER})_i + \beta_4(\text{EXPERSQ})_i + \beta_5(\text{URBAN})_i + \beta_6(\text{MARRIED})_i + \beta_7(\text{OTHERINC})_i + \beta_8(\text{BLACK})_i + \beta_9(\text{HISPANIC})_i + \beta_{10}(\text{FEMALE})_i + \beta_{11}(\text{HIGHSCHL})_i + \beta_{12}(\text{SOMECOLL})_i + \beta_{13}(\text{COLLDEGR})_i + \beta_{14}(\text{COLLPLUS})_i + \beta_{15}(\text{KIDSU5})_i + \beta_{16}(\text{FAMSIZE})_i + \beta_{17}(\text{UNABHLTH})_i + \beta_{18}(\text{OIinFAM})_i + \beta_{19}(\text{MIinFAM})_i + \beta_{20}(\text{ADLDIFF})_i + \beta_{21}(\text{MIinFAM} \times \text{MULT})_i + \beta_{22}(\text{MIinFAM} \times \text{PHYS})_i + \beta_{23}(\text{MISPOUSE})_i + \beta_{24}(\text{MIinFAM} \times \text{OTHERINC})_i + \epsilon_i \qquad (2)$$

where AGESQ is the squared value of the *i*th person’s age, and EXPERSQ is the squared value of the *i*th person’s years of work experience. This variable for work experience, due to data limitations, is a proxy calculated as age minus years of education minus six (the age at which the individual

*An update to this survey (the Medical Expenditure Panel Survey) is currently being gathered by the Agency for Health Care Policy and Research, and the first two rounds of the data have been released. However, these rounds contain only household information; data on health conditions will not be available until round three is released, sometime in 1999 or 2000.

†This manner of defining mental illness is adopted to focus on individuals ill enough to likely require care. Approximately 7% of individuals in NMES are found to have a mentally ill family member using this ‘narrow’ definition. Other studies have used a broader definition and have therefore found a higher incidence of mental illness in the United States. For example, Kessler *et al.*[1] create an algorithm to detect mental illness using a battery of survey questions similar to the ones in NMES (reflecting an individual’s feeling ‘down’, ‘nervous’ or ‘depressed’). This method estimates that 30% of individuals are annually afflicted with psychological disorders.

Table 1. Variable definitions and weighted descriptive statistics from NMES subsample (9111 observations)

Variable name	Definition	Mean value	Standard deviation
Labor force variables			
LFP	= 1 if labor force participant; 0 otherwise	0.8261	0.38
EMPLOYED	= 1 if currently working; 0 otherwise	0.7777	0.42
LOGHOURS	log of weekly hours worked at most recent job	1.33	1.07
WAGE	hourly wage rate of most recent job	6.67	6.67
Sociodemographic variables			
AGE	age of person divided by 100 (0.18–0.64)	0.3397	0.11
FEMALE	= 1 if female; 0 otherwise	0.5062	0.50
BLACK	= 1 if black, non-Hispanic; 0 otherwise	0.0985	0.30
HISPANIC	= 1 if Hispanic; 0 otherwise	0.0826	0.28
URBAN	= 1 if in SMSA; 0 otherwise	0.7484	0.43
OTHERINC	weekly family income minus personal earnings/100	5.45	5.70
Time cost variables			
MARRIED	= 1 if married, spouse present; 0 otherwise	0.6904	0.46
KIDSU5	= 1 if kids under age 5 present in family; 0 otherwise	0.2301	0.42
FAMSIZE	number of persons in family residing in unit (2–14)	3.46	1.35
OIinFAM	= 1 if at least one family member is chronically physically ill or disabled; 0 otherwise	0.3718	0.48
Mental illness variables			
MIinFAM	= 1 if at least one family member has been diagnosed as mentally ill; 0 otherwise	0.0708	0.26
MIADLDIF	= 1 if mentally ill family member has at least one ADL limitation; 0 otherwise	0.0028	0.05
MIMULT	= 1 if mentally ill family member has multiple mental illnesses; 0 otherwise	0.0028	0.05
MIPHYS	= 1 if mentally ill family member has a chronic physical illness as well; 0 otherwise	0.0282	0.17
MISPOUSE	= 1 if mentally ill family member is married; 0 otherwise	0.0443	0.21
Human capital variables			
EXPER	age minus years of education minus 6/100	0.1527	0.12
UNABHLTH	= 1 if health limits kind of work; 0 otherwise	0.0419	0.20
HIGHSCHL	= 1 if twelve years of schooling completed; 0 otherwise	0.3902	0.49
SOMECOLL	= 1 if years of schooling >12 and <16; 0 otherwise	0.2268	0.42
COLLDEGR	= 1 if sixteen years of schooling completed; 0 otherwise	0.1157	0.32
COLLPLUS	= 1 if more than sixteen years of schooling; 0 otherwise	0.0784	0.27

Source: Unpublished results based on the National Medical Expenditure Survey, 1987.

should have started schooling). Previous research indicates a quadratic relationship between age and LFP and between experience and LFP, so including AGESQ and EXPERSQ best captures the effects of age and experience on LFP.[25]

Tobit Regression

My second equation is a censored regression model, or tobit, with the log of weekly hours (LOGHOURS) as the dependent variable. Only individuals in the labor force will be included in this second stage of the analysis, so the analysis in this section is 'conditional' upon an outcome from the first stage (LFP = 1). I need to drop those individuals in my subsample who are not in the labor force, leaving me with 7471 observations for this analysis. Those who are in the labor force but unemployed have been assigned a zero value for LOGHOURS.* Thus, the distribution of LOGHOURS will be censored at zero, generating the need for a Tobit model in this stage.†

The logged value of hours worked is used in the regression since it is more likely to have a normal distribution than hours itself, which tends to be highly skewed. The explanatory

*Because I cannot transform zero values by log in the Tobit regression stage, I assign a zero value to LOGHOURS for the purpose of the regression, so the log transformation has already taken place for individuals who do not work. Thus, LOGHOURS=zero for those who are not working and LOGHOURS=log(hours) for those who are working.

†Of those determined to be in the labor force, 6% are unemployed. Although a current wage and current weekly hours are not available for those unemployed, the data does provide the researcher with 'wage earned at most recent job' and 'weekly hours worked at most recent job'. These variables are used to proxy for the missing current information for those who are in the labor force but unemployed.

variables included are those that have frequently been found to have an effect on LOGHOURS, with the addition of measures of mental illness in the family. I am primarily interested in the sign and magnitude of the coefficients on the mental illness variables as they indicate the impact of having a mentally ill family member on hours worked, all else equal. The tobit equation is defined as follows:

$$\text{LOGHOURS}_i = \alpha_0 + \beta_1 (\text{AGE})_i + \beta_2 (\text{AGESQ})_i + \beta_3 (\text{EXPER})_i + \beta_4 (\text{EXPERSQ})_i + \beta_5 (\text{URBAN})_i + \beta_6 (\text{MARRIED})_i + \beta_7 (\text{OTHERINC})_i + \beta_8 (\text{BLACK})_i + \beta_9 (\text{HISPANIC})_i + \beta_{10} (\text{FEMALE})_i + \beta_{11} (\text{HIGHSCHL})_i + \beta_{12} (\text{SOMECOLL})_i + \beta_{13} (\text{COLLDEGR})_i + \beta_{14} (\text{COLLPLUS})_i + \beta_{15} (\text{KIDSU5})_i + \beta_{16} (\text{FAMSIZE})_i + \beta_{17} (\text{UNABHLTH})_i + \beta_{18} (\text{OIinFAM})_i + \beta_{19} (\text{MIinFAM})_i + \beta_{20} (\text{ADLDIFF})_i + \beta_{21} (\text{MIinFAM} \times \text{MULT})_i + \beta_{22} (\text{MIinFAM} \times \text{PHYS})_i + \beta_{23} (\text{MISPOUSE})_i + \beta_{24} (\text{MIinFAM} \times \text{OTHERINC})_i + \beta_{25} (\text{WAGE})_i + \beta_{25} (\text{MIinFAM} \times \text{WAGE})_i + \epsilon_i \qquad (2)$$

where the variables WAGE and MIinFAM × WAGE are included as additional regressors (as compared to the probit equation). Again, AGESQ and EXPERSQ are included to best capture the effect of age and experience on LOGHOURS.

Sample Selection Model

As discussed by Heckman in his original sample selection research, there is potentially a selection bias problem with the estimates derived from the 'conditional' tobit model.[26] If the individuals who *select* themselves as participants in the labor market have some unmeasured characteristic that is correlated with the number of hours they work, then this problem of self-selection results in biased parameter estimates. Thus, I estimate a two-equation sample selection model to control for the possibility of selection bias.

The sample selection model utilizes a maximum likelihood estimation (MLE) method to allow the error terms to be correlated across the probit and tobit equations. This controls for the possibility of some unobservable, omitted variable that contributes to *both* a person's probability of being in the labor force *and* their hours worked. The parameter rho (ρ) estimates the correlation between the error terms of the probit and tobit analyses. If the MLE estimate of the correlation coefficient ρ is found to be significant, then sample selection is present and corrected for in the model. In addition, likelihood ratio tests are performed between the two models (independent vs. correlated errors) to verify the proper specification.

Partitioning the Data

In the general model, the direction of the impact of the gender variable is ambiguous. To allow the coefficient estimates for the probit and tobit equations to vary for females and males, I partition the data by gender and estimate the models independently for each group. Then, a test for structural change will determine whether the estimated coefficients are significantly different between the two groups. This data partitioning may be important because studies have shown that for women, being married and having young children typically has a negative effect on labor supply. For men, the effect of these factors on labor supply is typically positive.[27]

Empirical Results

The results in this section are obtained from the general empirical model, which includes the independent probit and tobit analyses, and maximum likelihood estimation of the Tobit model with sample selection.* Then the estimates obtained from partitioning the data by gender are presented and discussed.

Probit Results

The results of the probit analysis are provided in **Table 2**. The main focus is on the mental illness indicators MIinFAM, MIinFAM × OTHERINC, MIMULT, MIADLDIF, MIPHYS and MISPOUSE. The first three indicators are estimated to have a negative impact on LFP, while the latter three are found to have a positive effect. For MIinFAM this finding indicates that the presence of a mentally ill family member may increase an individual's value in the home and reduce their propensity to be in the labor force. Also, the negative marginal effect of MIinFAM × OTHERINC indicates that the greater the available amount of other income for those who do have a mentally ill family member, the lower the probability of being in the labor force. The negative effect estimated for MIMULT indicates that multiple mental illnesses may cause an *additional* pull away from family members' labor market involvement. The positive estimates of the other three indicators imply that if the ill family member is married and has a functional difficulty or comorbid physical illness, individuals may be drawn *into* the labor force.

However, none of the estimated marginal effects of the mental illness indicators are statistically significant at acceptable levels. Thus, the probit results do *not* support the hypothesis that caretaking responsibilities for a mentally ill family member will draw certain individuals out of the labor market or that this effect varies with the position of the ill family member or other available income. The insignificance of the illness severity measures indicates that, regardless of how functionally limited the family member is, any impact on LFP cannot be considered to differ significantly from zero.

Most of the marginal effect estimates for the control variables are statistically significant and have the expected signs. The positive estimate of the marginal effect of AGE

*Greene[28] cites the frequent incidence of heteroscedasticity in probit and tobit models. I estimated both models with heteroscedasticity using several specifications, but in each case found that the results do not differ significantly from the estimates reported here. The largest value of the likelihood ratio statistic for testing the homoscedasticity assumption in the probit model (χ^2 [20] = 0.896) and tobit model (χ^2 [20] = 14.68) leads to acceptance of the null (homoscedasticity) in *every* case, as the 95% critical value is 31.41.

Table 2. Probit and tobit analysis results, weighted. Dependent variable is LFP for probit and LOGHOURS for tobit

Variable name	Marginal effects		
	Probit results	General model tobit results	Selection model tobit results
No. of Observations	9111	7471	7471
CONSTANT	−0.102	2.924**	3.365**
AGE	2.818**	2.297	−0.095
AGESQR	−4.091**	−4.806**	−1.099
FEMALE	−0.201**	−0.234**	−0.064**
BLACK	0.010	−0.212**	−0.202**
HISPANIC	−0.001	0.023	0.026
URBAN	−0.013	0.006	0.015
HIGHSCHL	0.084**	0.202**	0.143**
SOMECOLL	0.110**	0.241**	0.155**
COLLDEGR	0.128**	0.292**	0.203**
COLLPLUS	0.164**	0.295**	0.195**
EXPER	−0.024	1.488	1.346
EXPERSQ	0.364	0.487	0.159
OTHERINC	−0.004**	−0.001	0.004**
FAMSIZE	−0.011**	−0.017**	0.009
MARRIED	0.010	0.124**	0.099**
KIDSU5	−0.082**	−0.021	0.047*
OIinFAM	0.005	0.009	0.013
UNABHLTH	−0.101**	−0.107**	−0.036
MIinFAM	−0.028	−0.084	−0.061
MIinFAM × OTHERINC	−0.001	0.003	0.010*
MIADLDIF	0.029	−0.554**	−0.635**
MIMULT	−0.063	−0.083	−0.011
MIPHYS	0.033	−0.142*	−0.164**
MISPOUSE	0.020	0.089	0.065
WAGE	—	0.0119**	0.008**
MIinFAM × WAGE	—	0.008	0.005
RHO	—	—	−0.956**
Pseudo R^2	0.447	—	—
R^2/*Adj.* R^2	—	0.119/0.116	0.121/0.118
Log Likelihood	−4294.90	−7736.41	−10696.33

Note: Marginal effects are partial derivatives with respect to the vector of characteristics, computed at the means of the Xs.
*Indicates significance at the 95% level for a two-tailed test.
**Indicates significance at the 99% level for a two-tailed test.
Source: Unpublished results based on the National Medical Expenditure Survey, 1987.

and the negative effect of AGESQR indicates the relationship between an individual's age and their probability of being in the labor force has an *inverted U* shape. The maximum value of this quadratic can be calculated using the coefficient estimates, which is found to be 52. This indicates that as people age from 18 to 52, their probability of being a labor force participant increases, but from 52 to 65 years of age their probability of being in the labor force declines. There are several reasons that might contribute to this finding. Foremost, people are nearing eligibility for retirement and have typically taken care of their responsibilities (e.g., raised their children, paid off their mortgage, become vested in a retirement plan), so the option of not working becomes a feasible one for more and more individuals as they age into their fifties and sixties.

The marginal probability estimates of each of the dummy variables indicating educational attainment are positive and the estimated marginal effect increases with each level, as expected. Likewise, estimates of the variables FEMALE, HISPANIC and OTHERINC are negative, as anticipated (although HISPANIC is statistically insignificant). MARRIED has a positive, although insignificant, impact on LFP, indicating that married individuals cannot be considered to have a higher propensity to be in the labor force, all else equal. The insignificance of this variable is not surprising, as MARRIED may have opposing effects for males and females. I anticipate that partitioning the data by gender will reveal a stronger effect for this variable.

Having a work-limiting health condition, UNABHLTH, negatively affects participation in the labor force, as expected. The FAMSIZE variable, which indicates the number of individuals in the family, has a negative and significant effect on LFP. This indicates that the time cost of a larger family reduces the probability of labor force participation, *ceteris paribus*. Likewise, the presence of a child under the age of five has a significant, negative impact on LFP.

For five of the variables, the marginal effect estimates do not have the expected signs, but each of these estimates do not differ significantly from zero at acceptable levels of significance ($\alpha \leqslant 0.05$). The race variable BLACK is expected to have a negative impact on LFP (considering that whites/Asians are the comparison race category) but is found to have a positive, insignificant effect. I expected that living in an urban area (URBAN) would have a positive effect on LFP, but the data in this study indicates a negative, insignificant effect.

Previous studies have found that work experience typically has a quadratic relationship with LFP, indicating a positive coefficient on EXPER and a negative coefficient on EXPERSQ.[25] However, I find that EXPER has a negative and EXPERSQ a positive, insignificant effect on LFP. Additionally, due to the time cost of dealing with a chronically ill family member, I expected OIinFAM to have a negative impact on LFP, yet the results here indicate an insignificant, positive effect.

Tobit Analysis

My second equation is a tobit regression, with the log of weekly hours as the dependent variable. The results of this analysis are also reported in Table 2. Focusing attention once again on the mental illness variables, the results indicate there is a negative impact of having a mentally ill family member on hours worked once the individual is already participating in the labor market. This is especially evident when the ill individual has activity limitations (MIADLDIF) or suffers a comorbid physical illness (MIPHYS), as the estimates of these measures are statistically significant. On the other hand, MISPOUSE has a positive impact on hours. This indicates that if the mentally ill family member is married, hours tend to increase. The interaction term MIinFAM $\times$ WAGE is positive and significant, revealing that those individuals with a mentally ill family member who have higher wages tend to work more hours, while those with lower wages tend to work fewer hours. These results are as expected, as the higher wage individuals have a higher opportunity cost of spending time providing care for the ill individual and are therefore likely to increase labor market time while lower wage individuals reduce work time (potentially to provide care). Thus, the data supports my hypothesis that

$$\left(\frac{\partial^2(\text{workhrs})}{\partial(\text{wage})\partial(\text{familln})}\right) > 0.$$

For most of the control variables used in the tobit, the signs of the marginal effects are as expected. Although MARRIED was found to have an insignificant impact on LFP, being married has a strong, positive effect on working hours. In this model, with no correction for self-selection bias, this can be the result of one spouse specializing in labor market work and the other specializing in home production. The one who spends the day in the labor market may work more hours, *ceteris paribus*, to recoup some of the lost earnings of the spouse who stays at home.

As in the probit analysis on labor force participation, AGE has a positive effect and AGESQ has a negative effect, indicating a quadratic relationship between age and LOGHOURS. The same justification holds here; up to a certain age individuals will work more hours as they grow older and at some age this tendency begins to fall so that hours decline as workers approach retirement age.

BLACK and FEMALE both have a significant, negative effect on LOGHOURS, as expected. Both URBAN and EXPER are positive, as anticipated, yet neither is statistically significant. As was the case with the LFP probit, each of the four education dummies is positive and highly significant, indicating that more schooling leads to working more hours. As predicted, OTHERINC and KIDSU5 are found to have a negative impact on LOGHOURS, although each is insignificant. FAMSIZE and UNABHLTH both have significant, negative effects on LOGHOURS, indicating that the time cost of a larger family, all else equal, reduces hours of market work, while individual health limitations curtail time at work as well.

The hourly wage is included as an additional regressor in the hours equation, and WAGE is found to have a positive, significant impact on LOGHOURS. This result indicates that a higher wage leads to more hours of work so that the substitution effect (substituting away from the relatively more expensive leisure toward more work) outweighs the income effect for these labor force participants. Given that the average wage of the sample is a relatively low \$7.84 per hour, this result is not surprising.

Only three control variables do not have the expected signs: HISPANIC, EXPERSQ and OIinFAM. In each of these cases, however, the marginal effect is statistically insignificant (at $\alpha \leqslant 0.05$).

Sample Selection Model

The estimates derived from the conditional tobit model may be biased if the individuals who ‘select’ themselves as participants in the labor market have some unmeasured characteristic that is correlated with the number of hours they work. Thus, in this section, maximum likelihood estimation of a two-equation, sample selection model is estimated to control for the possibility of selection bias.

The sample selection model results are provided in the last column of Table 2. To determine whether or not the sample selection model is the appropriate specification, a likelihood ratio test is performed between the two models that have been estimated: model (1), probit and conditional tobit estimated as two separate equations (i.e., independent error terms), versus model (2), the two-equation sample selection model. Using the log-likelihood values reported for each model, the chi-squared statistic is:

$$\chi^2(20 = -2\ \{[(-4294.90) + (-7736/41)] - (-10696.33)\}$$
$$= 2669.96$$

which tells us to reject the null hypothesis that the error terms are independent, indicating the sample selection model *is* appropriate.

After controlling for selection bias the marginal estimate of MIinFAM is still found to be negative in explaining the variation in LOGHOURS and is still statistically insignificant. This indicates that the tendency for family members of the mentally ill to reduce their hours of work, after controlling for the decision to participate in the labor market, does not differ significantly from zero. Further, the interactive variable MIinFAM × WAGE also remains positive but is now insignificant in the selection model. Thus, by accounting for selection bias, the support for the hypothesis that family members of the mentally ill work more hours if they have higher wages is absent.

The variable MIinFAM × OTHERINC is found to be significant and positive, indicating that those individuals with mentally ill family members tend to work more as OTHERINC rises. This suggests that other family income can be used for providing care for the mentally ill family member, thereby reducing the need for the individual to reduce work hours. The positive impact estimated for MISPOUSE indicates that the presence in the family of a married adult diagnosed with a mental illness may increase hours of work for family members as they attempt to compensate for lost income. However, the effect is not considered different from zero at acceptable levels of significance ($\alpha \leqslant 0.05$).

In order to sort out the full effect of a mental illness in the family on hours of work, refer to the 'evaluated' marginal effects of each of the mental illness indicators provided in **Table 3**. To use these results, I first determine the applicable characteristics and then sum the effects for those attributes. To calculate the effect of only the significant factors, consider an individual who has a mentally ill family member with an ADL difficulty, a comorbid physical illness and average OTHERINC. The full effect is derived by summing the evaluated effects of each of those variables (and transforming back to hours from LOGHOURS) to obtain the total estimated impact on hours of work per week, in this case –0.76. On the other hand, policy makers may be interested in the sum of *all* the evaluated effects, whether deemed statistically significant or not. This total is estimated to be a loss of 0.58 hours per week.

There are several differences in the estimates of the control variables when moving from the independently estimated model to the sample selection model. In the latter specification, the effects of AGE, AGESQ, FAMSIZE and UNABHLTH on working hours become insignificant. This indicates that selection bias was creating a significant relationship between AGE and LOGHOURS, FAMSIZE and LOGHOURS, and UNABHLTH and LOGHOURS which, once controlled for, does not exist.

The sign on OTHERINC changes to positive and is statistically significant. This result is counterintuitive because an increase in unearned income, *ceteris paribus*, is expected to have a pure income effect on labor supply; individuals demand more 'leisure' time, if a normal good, when income rises.

Results from Partitioning the Data

In this section, I report the results of partitioning the data by gender. Because empirical research has demonstrated that males and females have very different ties to the labor market, segregating the data by gender may provide clearer results.[21] Several of the right-hand side variables in the model are theoretically ambiguous in their effects on labor market involvement due, perhaps, to opposing effects for males and females. Thus, this partition should clarify the effects of the variables for each gender. Tests of structural change are undertaken to determine if the partition improves the estimation of the model.

The necessary statistics and results of testing for structural change by gender partitioning are provided in **Table 4**. Notice that in each case the test statistic exceeds the 99% critical value of 37.57 so that the null hypothesis—that the two sets of coefficients are statistically equal—is rejected. Thus, partitioning by gender *improves* the estimation in both the probit and tobit equations, as well as in the sample selection framework.*

Table 4. Test of structural change—gender partition

Log likelihood values	Probit	Tobit	Tobit with selection
Restricted model—full data set	−4294.90	−7736.41	−10 696.33
Unrestricted model—females + males	−3359.43	−7592.63	−7408.19
χ^2 (20)	1870.94	287.56	6576.28

*Again, the model was tested for heteroscedasticity using several specifications, but in each case I found that the results do not differ significantly from the estimates reported here. The largest value of the likelihood ratio statistic for testing the homoscedasticity assumption in the probit model (χ^2 [20] = 0.826 for females and 2.62 for males) and tobit model (χ^2 [20] = 8.498 for females and 24.40 for males) leads to acceptance of the null (homoscedasticity) in *every* case, as the 95% critical value is 31.41.

Table 3. Evaluated marginal effects to determine full effect of mental illness on LOGHOURS

Variable	MIinFAM	MIinFAM × OTHERINC	MIADLDIF	MIMULT	MIPHYS	MISPOUSE	MIinFAM × WAGE
Marginal effect	−0.061	0.010*	−0.635**	−0.011	−0.164**	0.065	0.005
Mean value	1.000	5.703	0.040	0.039	0.399	0.626	6.421
Evaluated effect	−0.061	0.057	−0.0254	−0.001	−0.065	0.041	0.032

These results point to the necessity of separating the observations in the data set by gender to improve upon the estimates obtained from the model. Because gender partitioning is needed, the remainder of this section discusses the major differences found among the estimates for women and men.

The separate probit and tobit results are reported in **Table 6** for females and males. Note that the Tobit results for females are independently estimated as the sample selection model is not statistically different from the independent model. However, for males, the sample selection model significantly improves the results, so the Tobit with selection estimates are reported.†

Comparing the marginal effects for each of the explanatory variables across the sexes, notice that MIinFAM has a negative but insignificant effect on the probability of labor force participation for *both* females and males. This is surprising because other studies have found that 70% of caregivers are female.[29] Thus, I would expect females to have a greater tendency to withdraw from the labor force in the presence of MIinFAM, all else equal.

The results of partitioning the data for the hours equation indicate there is no significant impact of MIinFAM on hours for females *or* males, but the other indicators do reveal some disparity. A mentally ill family member with an ADL difficulty has a negative and significant impact on the hours of both females and males in the labor force, but *the magnitude of the effect is greater for males*. Only females significantly reduce work hours due to a family member with multiple mental illnesses, while only males are estimated to significantly decrease time at work when a mentally ill family member has a comorbid physical illness.

Prior studies have not adequately controlled for wage effects in the presence of an ill family member. This is significant in examining men's response to a mentally ill family member. The interactive variable MIinFAM $\times$ WAGE in the tobit regression has a different effect based on gender. Although WAGE is a stronger positive determinant of hours for females, MIinFAM $\times$ WAGE is insignificant. However, for males this interactive variable is positive and significant. This indicates that men who have mentally ill family members work more hours as their wages increase, all else equal. Thus, MIinFAM $\times$ WAGE only significantly increases the hours of males, indicating that my hypothesis that $(\partial^2(\text{workhrs})/\partial(\text{wage})\partial(\text{familln})) > 0$ is found to hold only for the male sample.

When I carefully control for the general effects of MIinFAM, including severity measures and the position of the ill individual in the family, as well as MIinFAM $\times$ WAGE, I find that MIinFAM reduces men's hours of work. This is partially offset by the increase in hours associated with the wage. Thus, to assess the *full* effect of mental illness for women and men separately, I need to evaluate the marginal effects at the means for each characteristic.

In order to determine the full effect of a mental illness in the family on hours of work, policy makers would need to consider the marginal effects (evaluated at the means of each indicator for the subsample of individuals who have mental illness present in their family) of each of the mental illness variables (see **Table 5**).

Once again, to estimate these 'evaluated' marginal effects, I first determine the applicable characteristics and then sum the effects for those attributes. For example, if I have a mentally ill family member who has an ADL difficulty, has a comorbid physical illness, and has average OTHERINC, I would sum the evaluated effects of each of those variables to get the total estimated impact on LOGHOURS, which when transformed back to hours is −1.64 hours per week for females and −1.96 hours per week for males.

Comparison of the total evaluated effects reveals that the impact on women is −0.45 and that on men is −0.75 hours per week. If only statistically significant effects are used, the impact on women is −1.01 and that on men is −0.93 hours per week. Because these figures are of similar magnitude, they indicate that *males should not be ignored when estimating the opportunity cost of illness to families*.

Table 5. Evaluated marginal effects to determine full effect of mental illness on LOGHOURS, by gender

Variable	MIinFAM	MIinFAM × OTHERINC	MIADLDIF	MIMULT	MIPHYS	MISPOUSE	MIinFAM × WAGE
Marginal effect for:							
females	0.076	−0.010	−0.468**	−0.529**	0.036	0.019	−0.002
males	−0.114	0.008	−0.678**	0.227	−0.255**	0.122	0.011**
Mean for:							
females	1.000	6.990	0.042	0.051	0.393	0.569	4.556
males	1.000	4.766	0.039	0.031	0.403	0.667	7.779
Evaluated effect for:							
females	0.076	−0.070	−0.020	−0.027	0.014	0.011	−0.009
males	−0.114	0.038	−0.026	0.007	−0.103	0.081	0.086

†The chi-square statistic for testing the selection model is 0.298 for females and 1198.6 for males. Thus, the selection model is appropriate for the male sample only.

Table 6. Separate estimation results for females and males, weighted

Variable name	Marginal effects—females		Marginal effects—males	
	Probit	Independent tobit	Probit	Tobit with selection
No. of observations	4732	3424	4379	4047
CONSTANT	−0.288*	2.827**	−0.135**	3.578**
AGE	4.063**	0.631	1.315**	−0.489
AGESQR	−6.058**	−3.889	−1.843**	−0.250
BLACK	0.025	−0.190**	−0.011	−0.218**
HISPANIC	−0.018	0.061	0.006	−0.027
URBAN	−0.034**	−0.012	0.001	0.011
HIGHSCHL	0.130**	0.320**	0.034**	0.058
SOMECOLL	0.203**	0.363**	0.017*	0.104**
COLLDEGR	0.197**	0.443**	0.042**	0.109
COLLPLUS	0.313**	0.408**	0.022	0.129
EXPER	−0.620	2.698*	0.129	0.632
EXPERSQ	1.656	−0.204	−0.175	0.683
OTHERINC	−0.003**	−0.004*	−0.001**	0.006**
FAMSIZE	−0.022**	−0.016	−0.001	−0.006
MARRIED	−0.075**	0.052*	0.050**	0.142**
KIDSU5	−0.180**	−0.117**	−0.006	0.039
OIinFAM	0.006	0.023	−0.004	−0.007
UNABHLTH	−0.119**	−0.079	−0.061**	0.010
MIinFAM	−0.022	0.076	−0.019	−0.114
MIinFAM × OTHERINC	−0.005	−0.010	−0.001	0.008
MIADLDIF	0.240	−0.467**	−0.008	−0.678**
MIMULT	−0.136	−0.529**	−0.016	0.227
MIPHYS	0.049	0.036	0.028*	−0.255**
MISPOUSE	0.054	0.019	−0.008	0.122
WAGE	—	0.032**	—	0.006**
MIinFAM × WAGE	—	−0.002	—	0.011**
Pseudo R^2	0.423	—	0.425	—
R^2/Adjusted R^2	—	0.098/0.092	—	0.115/0.109
Log likelihood	−2523.73	−3887.37	−1175.46	−4283.91

*Indicates significance at the 95% level for a two-tailed test.
**Indicates significance at the 99% level for a two-tailed test.
Source: Unpublished results based on the National Medical Expenditure Survey, 1987.

Note that prior studies included fewer control variables such as KIDSU5, FAMSIZE and EXPER. Therefore, my results may be a better estimate of the effect of family illness, holding these other factors constant. These findings indicate that males can be significantly affected and may hold important policy implications when assessing the costs of mental illness.

Conclusion

This study has examined the impact of mental illness on the labor market performance of family members of afflicted individuals. Previous research was surveyed to determine the contributions that could be made in the current study. A general theoretical model was developed to derive testable hypotheses. Estimates were obtained of the impact of a mentally ill family member on the probability of labor force participation and on weekly hours of work. The data was partitioned by gender to neutralize the potential problem of offsetting effects for females and males.

In this study, I have found that none of the mental illness indicators are important factors in determining probability of labor force participation. However, *after controlling for self-selection, hours of work are significantly affected by the presence of mentally ill family members*.

These findings only partly coincide with those of previous research. Wolf and Soldo[30] estimated that the presence of elderly parents (potential care receivers) did not significantly affect the probability of labor force participation of married women. However, they found that hours of work were not significantly affected either. Likewise, Ettner[16,17] did not find significant reductions in hours of work for caregivers. Thus, this research is unique in that significant reductions in hours of work are estimated when mental illness is present in the family.

Partitioning the data by gender was found to be appropriate.

Only males were found to experience a significant impact on their probability of labor force participation. When a male has a mentally ill family member with a comorbid physical illness, his LFP probability is estimated to *rise* by about 1.2%. The impact of family mental illness on the LFP rate of females was not found to differ significantly from zero. Females who have mentally ill family members were found to significantly reduce their hours, however, when the ill family member had an ADL difficulty or multiple mental illnesses. On the other hand, males with mental illness in the family cut back on their hours if the ill individual had an ADL difficulty or a comorbid physical illness, and they increased their hours if they had a relatively higher wage.

The estimates obtained in this study show that women and men need to be studied separately when determining the effects of family illness on labor supply. However, both are affected by significant amounts, indicating that men should not be ignored when trying to estimate the opportunity costs of mental illness in the family.

Current federal and state policies provide for some of the medical costs and replace some of the lost income of the ill individuals, but generally they do not support family members who are negatively affected by the illness. This research provides evidence supporting the arguments of advocates for policy to ameliorate the financial burden borne by family members of the ill. Policy makers will have to decide if the appropriate action is to provide in-kind services (day-care centers, home health care etc) or financial support (tax cuts, income subsidies etc). Design of the policy will need to include decisions regarding eligibility criteria and level of support.

I envision several extensions of this research. In this study, *any* diagnosed mental illness is used to determine whether mental illness is present in the family. Many of these individuals may not be severely impaired and may be functioning relatively well under a doctor's care and with the assistance of medication. Thus, examining particular mental illnesses to see if there is a higher cost of one over the other (e.g., schizophrenia versus major depression) may provide valuable information to policy makers. Also, comparison of the costs of psychological disorders to chronic physical illnesses (such as cancer and heart disease) should be undertaken.

I also expect to undertake further study of the significance of the position of the ill family member. For example, I want to examine whether an individual's position can indicate if there is a *direct* earnings loss to the family due to the illness (for example if a spouse becomes ill versus a child or elderly parent) that others may try to compensate for by working more.

Another vein of this research is to examine the medical care utilization of family members of the ill. If mental illness in the family creates stress for family members, we may observe higher rates of health care utilization. Office visits, hospitalization, home health care visits, emergency room visits and outpatient treatment are types of utilization that are available for this data set.

This study has been completed with the most comprehensive source of data currently available. However, when a more recent survey containing the necessary information is available, it will be interesting to see whether re-estimating these effects with newer data provides larger impacts. The updated version of NMES currently being compiled—the MEPS panel data set—will enable controlling for individual characteristics that are unobserved by taking advantage of the multiple observations over time. Estimating the impact for only severe mental illnesses is likely to increase the magnitude of the results as well.

References

1. Kessler RC, McGonagle KA, Zhao S, Nelson CB, Hughes M, Eshleman S, Wittchen HU, Kendler KS. Lifetime and 12-month prevalence of DSM-III-R psychiatric disorders in the United States. *Arch. Gen. Psychiatry* 1994; **51**: 8–19.
2. Franks DD. Economic contribution of families caring for persons with severe and persistent mental illness. *Admin. Policy Mental Health* 1990; **18**: 9–18.
3. Hodgson TA, Meiners MK. Cost-of-illness methodology: a guide to current practice and procedures. *Milbank Memorial Fund Q.* 1982; **60**: 429–462.
4. Hodgson TA. The state of the art of cost-of-illness studies. *Adv. Health Econ. Health Services* 1983; **4**: 129–164.
5. Fein R. *The economic costs of mental illness*. New York: Basic, 1958.
6. Luft HS. The impact of poor health on earnings. *Rev. Econ. Stat.* 1975; **57**: 43–57.
7. Bartel A, Taubman P. Health and labor market success: the role of various diseases. *Rev. Econom. Stat.* 1979; **61**: 1–8.
8. Cruze A, Kristiansen P, Collins J, Jones D. *Economic costs of alcohol and drug abuse and mental illness: 1977*. Research Triangle Park: Research Triangle Institute Press, 1981.
9. Harwood H, Napolitiano D, Kristiansen R, Collins J. *Economic costs of alcohol and drug abuse and mental illness: 1980*. Research Triangle Park: Research Triangle Institute Press, 1984.
10. Ettner SL, Frank RG, Kessler RC. The impact of psychiatric disorders on labor market outcomes. *National Bureau of Economic Research: Working Paper Series*. Working Paper 5989. 1997.
11. Rubin J, Wilcox-Gok V, Keoughan M. The effect of mental illness on the employment and earnings of family members. Unpublished working paper. Northern Illinois University, DeKalb, IL, 1995.
12. Salkever DS. Children's health problems and maternal work status. *J. Human Resources* 1982a; **17**(1): 94–109.
13. Salkever DS. Children's health problems: implications for parental labor supply and earnings. In: Fuchs VR, ed. *Economic aspects of health*. National Bureau of Economic Research, Chicago: University of Chicago Press. Ch. 8, 1982b.
14. Berger MC, Fleisher BM. Husband's health, wife's labor supply. *J. Health Econ.* 1984; **3**: 63–75.
15. Stone RI, Short PF. The competing demands of employment and informal caregiving to disabled elders. *Med. Care* 1990; **28**(6): 513–526.
16. Ettner SL. The impact of 'parent care' on female labor supply decisions. *Demography* 1995a; **32**(1): 63–80.
17. Ettner SL. The opportunity costs of elder care. *J. Human Resources* 1995b; **31**(1): 189–205.
18. Chirikos TN. Aggregate economic losses from disability in the United States: A preliminary assay. *Milbank Q.* 1989; **67**(2): 59–91.
19. Becker GS. A theory of the allocation of time. *Econ. J.* 1965; **75**: 493–517.
20. Abbott M, Ashenfelter O. Labour supply, commodity demand and the allocation of time. *Rev. Econ. Studies* 1975; **43**: 389–411.
21. Killingsworth MR. *Labor supply*. Cambridge: Cambridge University Press, Ch. 2, 1983.
22. Bryant WK. *The economic organization of the household*. Cambridge: Cambridge University Press, 1990.
23. Franks P, Nutting P, Clancy C. Health care reform, primary care, and the need for research. *J. Am. Med. Assoc.* 1993; **270**(12): 1449–1452.

24. Bartman B, Clancy C, Moy E, Langenberg P. Cost differences among women's primary care physicians. *Health Affairs* 1996; **15**(4): 177–182.
25. Polachek SW, Siebert WS. *The economics of earnings*, 1st edn. Cambridge: Cambridge University Press, 1993.
26. Heckman JJ. Sample selection bias as a specification error. *Econometrica* 1979; **47**: 153–161.
27. Ehrenberg RG, Smith RS. *Modern labor economics: Theory and public policy*, 5th edn. New York: Harper Collins, Ch. 12, 1994.
28. Greene WH. *Econometric analysis*, 2nd edn. New York: MacMillan, 1993.
29. Muurinen JM. The economics of informal care: Labor market effects in the National Hospice Study. *Med. Care* 1986; **24**(11): 1007–17.
30. Wolf DA, Soldo BJ. Married women's allocation of time to employment and care of elderly parents. *J. Human Resources* 1994; **29**(4): 1259–1276.

