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Work absences and doctor visits during an illness episode: The differential role of preferences, production, and policies among men and women

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ABSTRACT

This paper analyzes the absenteeism and medical care consumption behavior of employed men and women during an episode of acute illness. An individual's daily optimization decisions are modeled in a dynamic framework to evaluate the role of (1) preferences for absences and treatment, (2) effectiveness of these inputs on recovery, and (3) economic incentives in determining the number and timing of absences and doctor visits and the duration of illness. In general, men appear to be more responsive than women to changes in sick leave and health insurance mainly due to differences in preferences.

1. Introduction

The unscheduled work absence rate in the US reached its highest level since 1999 in 2006 at 2.5% of scheduled hours of work. These absences cost the average employer almost $660 per employee annually. Personal illness accounts for almost 40% of these work no-shows (CCH, 2006). Despite increasing costs of absenteeism, as well as current policy interest in employer-provided benefits and incentives (including sick leave and health insurance coverage), the economics literature has provided relatively few explorations of illness-related work absence decisions. During an illness, a sick employee must weigh the costs of missing work and/or seeking medical treatment with the benefits of recuperation and medical care consumption. A model of the determinants of behavior during an illness will shed light on the relative importance of preferences, constraints, health production, and policy variables.

In general, women are about 1.5 times more likely to be absent from work and experience a 50% higher percentage of lost scheduled work time than men. Much of the recent work on illness-related absenteeism, however, focuses on involuntary absences associated with long term illnesses (i.e., disability) as opposed to voluntary absenteeism related to minor acute departures from good health that also contribute to the high absenteeism rates. Our understanding of absenteeism behavior during acute illness episodes is limited without also considering medical care utilization. In this dimension, women similarly outpace men. Based on many measures of medical care utilization (e.g., expenditures, annual number of visits, frequency of use, etc.) women consume more medical care than men.

In addition to differential rates and types of illness that may explain gender differences in annual measures of absence and medical care consumption, the observed behavior of men and women during episodes of similar illness may differ for other reasons. Individuals have different preferences for missing work and seeking medical care. They face different constraints with regard to sick leave coverage and health insurance. Additionally, reduced work effort as well as medical treatment are productive inputs to the recovery process with potentially different marginal products. The observed differences in absenteeism and medical care utilization by gender suggest that the various contributors (i.e., preferences, constraints, and health production) have different impacts on the behavioral decisions of men and women.

This paper analyzes an employed individual's daily decisions to miss work and/or to visit a doctor during an episode of acute illness given his or her sick leave and health insurance coverage. Its purpose is not to identify individual or workplace correlates with the annual number of absences or medical care visits. It is not to explain frequency of absences or duration between absence spells. Rather, the goal is to understand differences among men and women in absence and medical care decision making *during* an episode of acute illness. I model this dynamic behavior as the sequential decision-making process of employed individuals solving a discrete choice, finite horizon, stochastic, and dynamic optimization problem. The model is estimated using data from the

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1987 National Medical Expenditure Survey (NMES). This data set has the unique feature of providing exact dates of illness contraction, recovery, work absence, and medical care use during the year, as opposed to only aggregated annual totals. The paper focuses on the effects of various policy alternatives on the work absenteeism and medical care consumption of men and women.

The findings suggest that the absenteeism and medical care utilization of men is more sensitive to changes in sick leave coverage and health insurance coverage than that of women. Despite the complementary relationship of absence and treatment in the recovery technology of both genders, the same policy alternative (e.g., full provision of sick leave and medical care coverage or restricted access to medical care) can produce different responses among men and women. This paper provides empirical evidence that decisions to be absent from work and to consume medical care are jointly made during episodes of acute illness and depend importantly on preferences, financial constraints, and recovery probabilities. As such, appropriate health insurance policy reform should consider the role of absenteeism, and hence sick leave coverage, on the behavior of sick workers.

The organization of the paper is as follows: A review of the relevant literature is presented in Section 2 and the contributions of this paper are highlighted. Section 3 presents the behavioral model describing absence and medical care decisions during an episode of acute illness. Section 4 describes the data used to estimate the structural parameters of the behavioral model. Section 5 discusses estimation results, and the behavioral responses of men and women to various public policy experiments are explored in Section 6. Section 7 concludes.

2. Review and contributions

This paper extends the literature on the demand for absenteeism and the demand for medical care by exploring the role of preferences, economic incentives, and health production in a dynamic, forward looking framework. The dynamic issues that are overlooked in the relatively small literature on absenteeism by economists include the influence of illness severity on the timing and duration of absences within an episode, the dynamic effects of absence as a recuperative measure, and the dependence of sick leave coverage on past behavior and its implications for future wage replacement. Hazard function models have been used to model transitions from attendance to absence, but these lack a complete behavioral explanation of transitions between health states or circumstances that may create a need for absenteeism (Fichman, 1989; Harrison and Hulin, 1989; Barmby et al., 1991, 1996; Johansson and Palme, 2002). Many authors attempt to get around these omissions by categorizing absences as voluntary or involuntary. This classification, however, often leads to arbitrary assignment of behavioral outcomes that are the result of stochastic events and optimizing decisions.[1]

Non-illness related reasons for absenteeism include higher marginal values of leisure on certain days, dissatisfaction with the job, personal needs, and stress. Absences initiated for these reasons are often anticipated and are accounted for in coverage schemes chosen by employers. For example, voluntary absences associated with days surrounding holidays and special events should alter production only slightly if mechanisms are in place to cover these probabilistic periods of labor shortage. Similarly, involuntary absences resulting from serious illness for which work is not permitted may cause only minor disruption to production if a firm correctly anticipates these rare but certain (in terms of workloss) events. Minor or temporary departures from good health that lead to unexpected and short-term absences, however, may be more costly for employers and employees alike. While a firm experiencing temporary, unexpected labor shortages may hire a replacement worker or shift production inputs/schedules, almost 40% of firms allow work to go undone or miss deadlines when absence occurs (IBI, 2006). The absenteeism literature, however, tends either to ignore the current state of health of a worker completely or to control only for general health status of an employee.[2] The latter approach that attempts to control for general health levels, while an improvement, fails to capture the changes in health over time (i.e., getting sick) that precipitate absence.

Several papers in the absenteeism literature stress the importance of contractual arrangements, or economic incentives, on absence behavior (Chaudhury and Ng, 1992; Barmby and Treble, 1994; Brown, 1994; Johansson and Palme, 1996, 2005; Broström et al., 2004). These analyses consider European benefits mostly, which, while applicable to short-term absences and temporary illnesses, extend to absence spells as long as 90 days and beyond. The firm-specific absence benefits in the US typically limit reimbursement to a fixed and small number of days or spells. It is unlikely that individuals who are absent from work due to serious adverse health outcomes (i.e., "involuntary" absences) will respond to incentives aimed at reducing or controlling short-run absenteeism. Changes in the sick leave coverage characteristics offered by US employers are more likely to influence "voluntary" absences associated with less severe illnesses. As stated by Brown and Sessions (1996, p. 42), "in order to analyze the unexpected behaviour of workers [...] attention should be drawn away from events which cause severe adverse health effects which may lead to long term or even permanent absence from work and towards the effects of day to day sickness". Evidence from Leigh (1989) indicates that acute illnesses such as colds and flu have the most influence on short-term illness-related absenteeism.[3]

It has been suggested that gender differences in absenteeism rates may reflect the greater investment in health among women relative to men (Paringer, 1983). In fact, Broström et al. (2004) find that economic incentives account for only about one-third of the male-female difference in work absence. They attribute most of the difference to "intrinsic gender behavioral differences" that are unobserved in their data. However, a structural analysis allows for measurement of underlying differences associated with preferences for absence as well as medical care during an illness, and those relating to recovery from illness (i.e., health production). Such health investment incentives are important components for understanding behavior while sick.

This paper uses as its starting point the structural analysis of employed men's behavior during an episode of acute illness found in Gilleskie (1998). That model explicitly incorporates the dynamic behavior associated with contraction of acute illness, absenteeism, medical care consumption, and recovery. Only five other papers to my knowledge (Crawford and Shum, 2005; Davis and Foster, 2005; Chan and Hamilton, 2006; Blau and Gilleskie, 2008; Khwaja, 2010) explain medical care and non-medical input decisions and

[1] For example, Kahana and Weiss (1992) assume that decisions to be absent can only be made when one is well; sick individuals are absent by definition.

[2] See Allen (1981), Paringer (1983), Leigh (1991), and Johansson and Palme (2002) as papers that incorporate discrete measures of health as explanatory variables. Barmby et al. (1994) allow for a continuum of health states. Johansson and Palme (1996) use a principal components analysis to account for variation in the occurrence of more serious, chronic, or work-impending illnesses such as heart attack, diabetes, and pregnancy. Vistnes (1997) finds that health status measures explain absenteeism more consistently than economic factors such as wages and sick leave coverage for both men and women.

[3] Acute conditions are characterized by a sudden onset, a sharp rise, and a short course (e.g., colds, flu). In contrast, chronic conditions are typically associated with a long duration or frequent recurrence over a long time (e.g., heart disease, migraine headaches).

their influence on health outcomes in a manner suggested in health economics' infancy by Grossman (1972). That is, rather than measuring correlations or estimating linearized demand functions or stand-alone production functions, these authors estimate the preferences, constraints, and expectations of forward-looking individuals in a framework that allows for evaluation of health policy alternatives.[4]

3. The behavioral model

3.1. Overview

The dynamic stochastic framework captures the daily work absence and medical treatment decision making of employed individuals during an acute illness episode. Individuals in this model occupy one of $K+1$ distinct health states: well ($k=0$) or sick with an acute illness of type k ($k=1,\ldots,K$). Illnesses may differ by the effectiveness of absence and treatment, by severity, by duration, and by discomfort, among other things. Even a specific observed diagnosis (e.g., acute nasopharyngitis or the common cold) may differ along these dimensions. The unobserved illness types allow for these unobserved differences.[5] When well, an individual faces a time-invariant probability, π^{S_k}, of contracting an acute illness of unobserved type k that depends on exogenous demographic and health-related variables.[6]

Given income, sick leave coverage, and health insurance, an individual decides, upon becoming sick, whether or not to be absent from work and whether or not to seek medical treatment. Absence or treatment may affect contemporaneous utility directly, as well as indirectly through the budget constraint. Additionally, absences may reduce the future wage replacement rate of those with sick leave coverage. By staying home from work or by seeking treatment, however, the individual may improve his chances of recovery (tomorrow and for all future days of the illness episode) from the type k illness. The recovery probability, π^{W_k}, captures the dynamic aspects of biological transition from a sick state to a well state and incorporates the endogenous effects of illness duration, work absence, and medical treatment. The effects of continuing to work and/or delaying treatment while ill are embedded in the recovery technology.

The decision-making process continues, with the same absence and treatment alternatives, until the individual recovers. An individual is assumed to work and not seek treatment while well. The stationery value of being well, however, depends on the probability of future illness and anything that affects absence and treatment behavior while acutely ill. Economic incentives (and constraints) include sick leave and health insurance coverage, wage replacement rates, coinsurance rates, income, and medical care costs.[7]

3.2. Alternatives, state variables, and illness transitions

The alternatives j available each day to an employed individual who is temporarily sick with acute illness type k are

$j=1$: work and do not seek treatment
$j=2$: work and seek treatment
$j=3$: do not work and do not seek treatment
$j=4$: do not work and seek treatment.

An indicator function, d_t^j, indicates the alternative chosen by an individual on day t of an illness where $d_t^j = 1$ if alternative j is chosen and $d_t^j=0$, otherwise. Alternatives are mutually exclusive such that $\sum_{j=1}^{4} d_t^j = 1, \forall t, t = 1,\ldots,T$, where T is the longest possible length of the acute illness episode. The analysis ignores preventive treatment, so employed individuals who are free from illness have no illness-related absences and no medical visits.

Information regarding previous decisions during the illness episode is available at the beginning of each day, and affects the value of different absence and treatment alternatives today. The observed state at the beginning of day t of an illness is described by a vector, denoted $\mathbf{z}_t$, of four episode-specific variables: the illness type, k; the elapsed length of the current illness, t; the accumulated number of illness-related absences from work, a_t, and the accumulated number of physician visits, υ_t, as well as exogenous individual-specific characteristics and past (within episode) shocks to preferences and illness transitions. The illness type (observed by the individual at the beginning of the illness episode but unobserved by the econometrician) remains fixed for the length of the episode, but the other variables evolve as continued illness is realized and absence and treatment decisions are made.

The probability of contracting illness type k is

$$\pi^{S_k} = \frac{\exp\left(\delta_{0k} + \boldsymbol{\delta}_{1k}'\mathbf{H}\right)}{\sum_{k'=0}^{K}\exp\left(\delta_{0k'} + \boldsymbol{\delta}_{1k'}'\mathbf{H}\right)} \tag{1}$$

where $\mathbf{H}$ is a vector of general health status and age. The probability of recovery after t days of illness type k is

$$\pi^{W_k}(\mathbf{z}_{t+1}) = \begin{cases} \dfrac{\exp\left(\boldsymbol{\eta}_k'\mathbf{E}_{t+1}\right)}{1+\exp\left(\boldsymbol{\eta}_k'\mathbf{E}_{t+1}\right)} & \text{if } t = 1,\ldots,T-1 \\ 1 & \text{if } t = T \end{cases} \tag{2}$$

$$\text{where } \boldsymbol{\eta}_k'\mathbf{E}_{t+1} = \eta_{0k} + \eta_{1k}a_{t+1} + \eta_{2k}(a_{t+1})^2 + \eta_{3k}\upsilon_{t+1} + \eta_{4k}(\upsilon_{t+1})^2 + \eta_{5k}(a_{t+1})(\upsilon_{t+1}) + \eta_{6k}t + \eta_{7k}(t)^2 + \eta_{8k}(t)^3 + \boldsymbol{\eta}_{9k}'\mathbf{H}.$$

The specification allows for non-linear marginal returns to absence and treatment, complementarity of the two endogenous inputs, and the biological effects of time and individual characteristics. Individuals recover with probability one after T days for the acute illnesses considered in this model and co-morbidities (multiple illnesses during one episode) are not modeled.

4 Chan and Hamilton (2006) model weekly treatment therapies of AIDS patients over two years. Crawford and Shum (2005) model monthly prescription drug decisions for gastro-intestinal illness. Davis and Foster (2005) model semi-annual mental health care decisions during childhood. Blau and Gilleskie (2008) model annual physician visits and hospital nights among the near elderly. Khwaja (2010) models annual smoking, exercise, drinking, and medical care decisions over an adult lifetime.

5 The National Medical Expenditure Survey (NMES) data classify acute illnesses broadly (e.g., infectious and parasitic diseases or respiratory conditions) as well as by the specific 4-digit ICD-9 code (e.g., influenza or acute bronchitis). The unobserved illness types defined in the model blend these two classifications (one with a few categories and one with a few hundred categories) to distinguish illnesses by common unobserved characteristics such as how absence intensive, treatment intensive, and severe the illnesses are.

6 It is assumed that an individual knows the type of illness that he has contracted. Learning about one's illness type is not considered here, but has been explored in a health context by Crawford and Shum (2005), Chan and Hamilton (2006), and Mira (2007). Additionally, the unobserved heterogeneity is specific to the illness episode and not to the individual. Hence, it should not be interpreted as permanent individual heterogeneity that affects both the values of being sick and well (although the well value function does depend on the distribution of future health states).

7 Although sick leave and health insurance coverage are assumed to be exogenous, I control for characteristics that influence these decisions such as income, health status, and age. The endogeneity bias, however, is likely to overstate the effects of sick leave and health insurance coverage on illness-related absenteeism and medical care use. See Gilleskie (1998) for a more detailed discussion of this omission.

3.3. Utility functions and budget constraints

The utility of an individual who is well, $U^W(\cdot)$, is deterministic and depends only on the composite consumption good, X_t. (The utility of being free of sickness is normalized to zero and the marginal utility of consumption is normalized to one.) The utility of an individual who is temporarily sick, $U^{S_k}(\cdot)$, depends on consumption, the type of acute illness, and the vector of work absence and medical care use choice indicators, $\mathbf{d}_t = (d_t^1, d_t^2, d_t^3, d_t^4)$, reflecting chosen alternatives on each day t of the illness episode. Alternative-specific random taste components of utility, $\boldsymbol{\epsilon}_{tk} = (\epsilon_{tk}^1, \epsilon_{tk}^2, \epsilon_{tk}^3, \epsilon_{tk}^4)$, additively affect an individual's utility while sick. These taste parameters represent information known by the individual but unobserved by the econometrician. In addition to being alternative specific, this idiosyncratic heterogeneity is also individual, time, and illness specific. The per-period linear-additive utility functions are

$$U^W(X_t) = X_t \quad \text{if well}$$

$$U^{S_k}(X_t, \mathbf{d}_t, \boldsymbol{\epsilon}_{tk}) = \alpha_{0k} + \alpha_{1k}(d_t^2 + d_t^4) + \alpha_{2k}(d_t^3 + d_t^4) + \alpha_{3k}X_t + \sum_{j=1}^{4} \epsilon_{tk}^j d_t^j \quad \text{if sick.} \tag{3}$$

In order to simplify notation, the utility of an individual who is sick with illness type k and choosing alternative j is denoted as $U_j^{S_k}(X_t, \boldsymbol{\epsilon}_{tk}^j)$ subsequently. The utility functions allow for utility (or disutility) associated with the temporary departure from being well, a direct utility gain or loss associated with visiting a doctor, the utility gain or loss of missing work, and differences in marginal utility of consumption by health state. Additionally, each of these marginal effects differs by the type of illness contracted.[8]

Each period individuals receive their per-day labor income Y minus income losses if the individual chooses to be absent from work. The variable L is a binary indicator of sick leave coverage that may replace lost wages. A replacement rate, $\Phi(\cdot)$, defines the proportion of the daily wage that sick leave replaces (if $L = 1$) and is a logistic function of the accumulated number of absences within the episode. Income is allocated between composite consumption, X_t (with a price normalized to one) and medical care. The product pC defines an individual's out-of-pocket cost of a medical visit, which reflects the total price p of a visit and the out-of-pocket coinsurance rate $C, C \in [0, 1]$, or the exogenous proportion of the total price for which an insured individual is responsible.[9] If an individual is uninsured, then he always faces the full price of medical treatment. More specifically, the absence-dependent wage replacement rate is

$$\Phi(a_{t+1}) = \frac{\exp(\phi_1 + \phi_2 a_{t+1})}{1 + \exp(\phi_1 + \phi_2 a_{t+1})} \tag{4}$$

and the budget constraint is

$$X_t = \begin{cases} Y & \text{if well} \\ Y - Y(1 - [\Phi(a_{t+1})]L)(d_t^3 + d_t^4) & \\ \quad - pC(d_t^2 + d_t^4) & \text{if sick.} \end{cases} \tag{5}$$

Conditional on sick leave and health insurance coverage, the objective of an individual who is sick with illness type k is to choose among the absence and treatment alternatives each day to maximize discounted lifetime expected utility. The function $V_j^{S_k}(\cdot)$ denotes the expected lifetime utility of an individual who is sick with an illness of type k and is choosing alternative j on day t of the illness. When sick with illness type k, the value of the jth alternative is $V_j^{S_k}(\mathbf{z}_t, \boldsymbol{\epsilon}_{tk}) = U_j^{S_k}(X_t, \epsilon_{tk}^j) + \beta\left[\pi^{W_k}(\mathbf{z}_{t+1})V^W + (1 - \pi^{W_k}(\mathbf{z}_{t+1}))V^{S_k}(\mathbf{z}_{t+1})\right]$. The expression V^W denotes the stationary expected lifetime utility of an individual when he is well ($t = 0$), where $V^W = U^W(X_0) + \beta\left[\left(1 - \sum_{k=1}^K \pi^{S_k}\right)V^W + \sum_{k=1}^K \pi^{S_k}V^{S_k}(\mathbf{z}_1)\right]$. The maximal expected value of utility when sick with illness type k, $V^{S_k}(\cdot)$, is defined to be the day t maximum of the expected lifetime utilities of choosing among the four alternatives during a period of illness; that is, $V^{S_k}(\mathbf{z}_{t+1}) = \mathrm{E}_t\left[\max_{j\in J}\left[V_j^{S_k}(\mathbf{z}_{t+1}, \boldsymbol{\epsilon}_{t+1k})\right]\right], \forall t$.

The theoretical model presented above describes the economic and biological behavior of individuals over an illness episode with regard to daily absenteeism and medical care consumption. Solution of the optimization problem yields probabilities of absence and treatment behavior. These choice probabilities along with illness recovery probabilities, illness contraction probabilities, and wage replacement rates (which are each estimated within the model) form the likelihood of observed outcomes. The appropriate likelihood function for estimation of these parameters is presented in the Appendix.

4. Description of the data

4.1. Description of the survey and sample selection

The 1987 National Medical Expenditure Survey (NMES) is a national probability sample of the civilian, noninstitutionalized population and contains detailed information on health status, medical care utilization, health insurance coverage, employment, sick leave, income, and demographics. It oversamples Blacks, Hispanics, and the poor to allow for more precise estimates of the medical care use and expenses for population subgroups that may be of particular policy interest. It has the unique distinction of recording detailed information about every illness episode accompanied by either a work absence or medical treatment.

8 The model is purposely silent about the source of the utility effects of absence and treatment. The model makes explicit the pecuniary costs of these decisions in the budget constraint, as well as the productive effects of these choices on illness recovery. The remaining contemporaneous effects of missing work reflected in the utility specification capture, perhaps, negative consequences such as making the boss or your co-workers angry or reducing your chances of promotion, or positive consequences such as minimizing the (dis)utility of sickness by laying in your own bed rather than working or reducing the spread of disease. The contemporaneous effects of seeking treatment might include the negative consequences of costly travel and waiting time or the positive consequences of relief of current symptoms. The model specifies these utility effects of absence and treatment as additive. Complementarity of absence and treatment is allowed in the recovery technology.

9 I do not incorporate deductibles, a common feature of health insurance at the time of data collection, in the theoretical model of individual behavior for several reasons. (1) The model is limited to decisions about one type of treatment for a specific set of illnesses. Deductibles, or dollars remaining in one's deductible, are less discerning: payments for *all* covered treatments of *all* covered illnesses reduce the remaining deductible. Accurate modeling of the effects of deductible remainders would require inclusion of every possible illness and every type of treatment. Modeling all of these health transitions and utilization decisions is beyond the scope of this paper. (2) Despite this, determination of the dollars remaining in one's deductible is difficult from a data perspective. Insurance plans vary significantly in terms of what procedures are covered and to what degree. Additionally, the beginning date of the accounting period in insurance contracts differs by plan. For example, some plans cover expenses from January to January; others start the insurance year in July. Because the NMES data span the 1987 calendar year, utilization of all services that may have reduced the remaining deductible are available only for those individuals whose insurance year begins in January. (3) Even if dollars remaining in one's deductible were available at the beginning of the illness and deductibles were included in the model, solution of the model would require calculation of the well value function for each discretized value of the deductible remainder at each time period. It would expand the model from a stationary problem in which decisions are made over a finite period to a lifetime decision-making problem.

Admittedly these data reflect the behavior of employed individuals 20 years ago, and some things relevant to this analysis have changed in the US workplace during two decades. Sick leave coverage is not one of them. In fact, absence policies are just as varying and firm-specific today as they were then. In an effort to standardize leave rules, the Family and Medical Leave Act was passed in 1993, but the benefit does not apply to short-term unexpected absences due to illness. There has been a recent trend of offering excused time off for children's sickness or school activities, but this analysis focuses only on the *illness-related* absences of the employee. The most meaningful change since the late 1980s has been the dramatic conversion of health insurance reimbursement from fee-for-service to managed care. Cost-sharing is now less likely to be defined by deductibles and coinsurance rates (producing a variable out-of-pocket cost as a function of total charge and past behavior), but by co-payments (consisting of a known, fixed out-of-pocket cost per visit) and in- and out-of-network pricing. This change, however, is not crucial to the conclusions drawn by this study since treatment for the acute illnesses that are analyzed is provided almost exclusively by primary care physicians who would be "in-network" today. Hence, the in-network or out-of-network treatment decision is not relevant here. Furthermore, because prices per visit do not vary in this analysis, the out-of-pocket cost defined by the coinsurance percentage of the total charge reflects, essentially, a co-payment per visit, as is common in most managed care plans. Finally, prices of medical care have risen faster than general inflation, and consequently real wages, during the past two decades. Hence, the relative tradeoff between medical care consumption and work absence is likely to be different.

Yet the detail in the NMES data with regard to daily illness behavior and exact dates of illness episodes is unmatched by more recent health surveys including the 1996-present Medical Expenditure Panel Survey (MEPS). Participants in the NMES were asked to keep a daily log of their behavior over the 1987 calendar year. Interviewers visited participants three or four times during the year in order to record behavior up to that date and to verify previously obtained information. The data include dates of all illness episodes, of all medical services use,[10] and of all disability days[11] that together provide a day-by-day account of behavior.

The sample used to estimate the model of episodic behavior consists of males and females age 25 to 64 who reported being employed (but not self employed) during each of the interview rounds. (See Table 1 for sample selection criteria.) The estimation sample consists of 3797 males and 3457 females. Of these, some are never sick (with the acute illnesses I consider), some contract the illnesses but do not miss work or seek treatment during the illness episode, and some have at least one absence or doctor visit during an episode of illness. Unfortunately, episode information (such as beginning and ending dates and classification of the illness) for illnesses in which the individual sought no medical treatment and reported no disability days is not recorded. Thus, the proportion of individuals in the estimation sample (or in the entire data set for that matter) who are "observed to have an acute illness" understates the true probability of contracting an acute illness. However, this censoring problem is explicitly accounted for in construction of the likelihood function because the model provides probabilities of the behavior that leads to censoring of "unmedicated" illness episodes.

Table 1
Sample selection information.

Selection criteria	Remaining sample size		
	Males	Females	Total
NMES participants	18094	20352	38446
Aged 25–64 years	8325	9734	18059
And employed full time, full year	6630	5578	12208
And completed Health Status Questionnaire	5287	4537	9825
And no federal insurance assistance	5069	4032	9101
And valid responses for key variables	4608	3929	8537
And no illness and/or at least one acute illness	4608	3929	8537
And no illness and/or at least one acute illness ($\leq$21 days)	4513	3792	8305
(% of all acute illnesses that are $\leq$ 21 days)	(97.9%)	(96.5%)	(97.3%)
And not self employed	3797	3457	7254
(% of those ill at most 21 days who are not self-employed)	(84.1%)	(91.2%)	(87.4%)

The acute illnesses considered in this analysis are acute conditions according to the International Classification of Diseases (ICD-9) and the condition code reported in the NMES data (US Department of Health and Human Services, 1980). In order to understand absence and treatment behavior over an episode of illness, as well as the transitions into and out of illness, I restrict attention to acute infectious and parasitic diseases and acute respiratory conditions. These acute conditions account for almost 60% of all acute conditions (Adams and Benson, 1992). Examples of these acute illnesses include influenza, acute bronchitis, strep throat, the common cold, etc.[12] Because the computational complexity of solution to the dynamic programming problem depends on the length of the decision-making behavior, I do not consider illness episodes that number 22 or more days.[13] 19.1% (726) of males and 22.6% (782) of females in the estimation sample are observed to experience an acute infectious, parasitic, or respiratory illness episode lasting at most three weeks at some point during the 1987 calendar year.

4.2. Classification and discussion of observed characteristics

Males and females from different demographic and economic backgrounds may exhibit differences with regard to contraction of illness, recovery from illness, absenteeism, and medical care utilization. Estimation of the model requires solution of the dynamic programming problem for each unique combination of characteristics describing individuals. Consequently, some measures of the observed heterogeneity of individuals are divided into discrete classes, rather than assuming a continuous outcome which undoubtedly would require solution of the model for each individual at every iteration of the parameters. The variables used to classify individuals into unique observed "types" are daily income, health insurance coverage, out-of-pocket responsibility, sick leave availability, health status, age, and gender.

Daily income consists of three classes: lower income, middle income, and upper income. A daily wage (in 1987 dollars) of less than \$70 (\$17,500 per year) and \$50 (\$12,500 per year) defines the

[10] Due to computational problems associated with modeling choices among numerous medical care alternatives, only physician visits are analyzed. These include all visits to a physician whether in his office, an outpatient setting, or the emergency room.

[11] Because all recorded absences have associated with them specific illness codes and episode lengths, measurement error with regard to determination of illness-related absences, as opposed to recreational absences, is unlikely.

[12] I focus on these illnesses because the policies I consider are most likely to influence absenteeism and medical treatment behavior during these "less serious" illness episodes. That is, the illnesses do not require extended periods of work loss or medical attention. Also, the health status variable in the NMES data set is collected only once during the survey period. Thus, it is necessary that the illnesses considered in this analysis do not alter one's general self-reported health status over time since changes in this variable are not observed. These acute illnesses, as opposed to chronic illnesses or injuries, are less likely to alter one's reported perception of his general health.

[13] Acute illnesses are often defined as episodes lasting at most 90 days. Of all individuals in the data with acute illness episodes, 90.7% were well by the end of 21 days. For those with valid responses to key variables, this figure is about 97%.

lower-income interval for males and females, respectively. Upper-income males are those with a wage rate greater than or equal to $125 per day ($31,250) and for females this figure is $90 per day ($22,500). Middle income for each gender is defined as incomes between the high and low cut offs. The median daily wages within each income classification are $48.00, $96.00, and $168.00 for males and $33.00, $66.00, and $112.00 for females.

An important policy variable in this analysis is sick leave coverage. While lengths of coverage and wage replacement rates characterize most employer sick leave plans, the data only indicate whether an individual has paid sick leave or not. Efforts to model the costs of depleting one's stock of sick leave are described in the model specification. The complications described in footnote 9 regarding medical care deductibles would be similar for stocks of sick leave if they were available.

Health insurance coverage is another important policy variable in this work. The NMES data indicate whether an individual is insured or not and the source of his coverage. It also provides the percent of the total medical care charge for which an insured person is responsible. For all individuals who sought treatment, the total price of care and the amount paid out-of-pocket by the individual are available. For an insured individual who has never sought treatment from a physician for an acute illness (either because he was sick but chose not to seek treatment or because he was not sick), information on the percent of the total bill for which he would be responsible is not available.[14] The discrete classifications of out-of-pocket responsitiblity for those insured individuals who seek treatment are 0%, 20%, and 100%, where anyone paying less than 10% out of pocket is assigned 0% and anyone paying over 90% out of pocket is assigned 100%. Twenty percent represents the median out-of-pocket percentage paid by the remaining insured individuals who sought treatment during the illness episode. The uninsured, a fourth class of insurance, pay 100% of the total charge for medical care.

A health status questionnaire was administered in one round which provides self-reported health status at one point in time as excellent, good, fair, or poor. Because of the small number of individuals reporting a poor health status, I group fair and poor health statuses together. Two age classes are considered: 25–44 years and 45–64 years. Table 2 describes the male and female sample according to particular observed characteristics. Although not disaggregated in this table, individuals who experience an acute illness and choose to be absent from work or to visit a physician at least once during the illness episode are more likely to have sick leave coverage, to be insured, to have higher incomes, and to be younger than those for whom an illness episode is not observed.

The percent of persons in fair or poor health is largest among lower-income males (13%) and decreases as income rises (11% and 6% for middle-income and upper-income males, respectively). Similarly, the percent of lower-income males reporting an excellent health status (25%) is much smaller than that of the middle- and upper-income groups (33% and 38%). A similar pattern arises for women, but a larger proportion report lower health levels (18% of low income women report a fair or poor health status). As expected, males with lower incomes tend to be younger (85%), while a higher percentage of older males (39%) report having higher incomes. There appears to be little correlation between age and income for females. Older males appear to have lower health status; 16% of older males report fair or poor health status while only 9% of younger males do. This is true among women also, but, again, the proportion reporting fair or poor health is higher (10% of young females and 24% of older females).

The prevalence of sick leave and health insurance coverage also differ by observed characteristics. While nearly all upper-income individuals have sick leave provisions through their employer (87% of males and 89% of females), less than half of the lower-income individuals have sick leave coverage. Females in the middle- and upper-income categories are more likely to be covered than males, but lower-income females are four percentage points less likely to have sick leave coverage than males.

Almost all of the upper-income individuals in the ill sample report being insured (99% of males and 98% of females), while 26% of the lower-income males are uninsured. Only 21% of low-income females report being uninsured. Among those who are insured, the average proportion paid out-of-pocket for those who are ill and who visit a physician at least once during the illness is available. A larger proportion of upper-income males report paying less than 10% of their medical charges (34%) compared to those with lower incomes (28%). This gap is even larger for females (36% vs. 23%). The negative correlation between income and coinsurance rate may not be so high if higher income individuals are more likely to seek treatment when ill and, as a consequence, more likely to exceed the deductible limit and hit the point where insurance is paying a fixed proportion of their medical care costs.

Males and females also differ in behavior. Of those individuals who are observed to have an acute illness episode, females appear to be sick one half day longer than males on average (7.35 days for males vs. 7.80 days for females). When disaggregated by length of episode, a larger number of medical treatment visits is associated with illness episodes of a longer duration. Any absences are relatively more likely in shorter episodes, but longer spells of absence are associated with longer illness episodes. Females have more physician visits but are less likely to be absent than males. When they are absent during an illness, however, females are absent longer.

5. Estimation results

5.1. Parameter estimates

I estimate the parameters of the individual's optimization problem by maximizing the likelihood function defined in the Appendix. The daily discount factor, β, is constant at 0.9997, which corresponds to an annual discount rate or time preference of ten percent. The cost of a physician visit is $35.00 and does not vary across the illness episode or across individuals.[15] The specifications of the illness and recovery probabilities follow that of Eqs. (1) and (2) and allow for two unobserved types of acute illness. The utility functions and budget constraints follow the specifications described in Eqs. (3)–(5). The baseline health status is excellent with dummy variables indicating whether an individual's health

14 The likelihood function is correctly constructed given the unobserved data on out-of-pocket responsibility for those insured individuals who do not seek treatment when sick or who are not observed to be sick. This correction is possible only because the behavior that defines availablility of the out-of-pocket rate data (or lack of it) is explicitly modeled (i.e., consumption of medical care sometime during the illness episode). Gilleskie (1998) provides the details.

15 Because the total cost of $35.00 represents the 1987 median physician visit charge for individuals who sought treatment, it is not an accurate measure of the cost of a visit, in general. It is not obvious, however, where the figure lies in the distribution of physician visit costs. Is it at the low end of the distribution, implying that individuals who do not go to a doctor face higher prices, or is it at the high end, implying that those who do seek treatment have more serious illnesses and possibly higher physician visit costs? The estimates were not sensitive to the choice of the mean or median total cost. The use of an average cost measure, however, does not incorporate all of the uncertainty in medical visits costs (i.e., low probability, high cost visits).

Table 2
Sample summary statistics.

Group	Male sample (3797)				Female sample (3457)			
	Prop	Median	Mean	St Dev	Prop	Median	Mean	St Dev
Daily income								
Lower	0.35	48	47.24	15.79	0.40	33	32.15	10.92
Middle	0.40	96	95.51	15.53	0.39	66	66.40	11.29
Upper	0.25	168	185.85	88.29	0.21	112	126.70	49.32
Sick leave								
Available	0.68				0.67			
Not available	0.32				0.33			
Health insurance								
Insured	0.88				0.90			
Uninsured	0.12				0.10			
Health status								
Excellent	0.33				0.29			
Good	0.55				0.57			
Fair/Poor	0.12				0.14			
Age								
25–44 years	0.69	34	33.82	5.56	0.68	34	33.96	5.62
45–64 years	0.31	52	52.87	5.64	0.32	53	53.37	5.60
Physician visits								
# $\geq$0, per episode	1.00	0	0.09	0.34	1.00	0	0.13	0.39
# >0, per episode	0.08	1	1.13	0.44	0.12	1	1.12	0.44
Work absences								
# $\geq$0, per episode	1.00	0	0.27	0.87	1.00	0	0.32	0.96
# >0, per episode	0.14	1	1.91	1.50	0.16	2	2.04	1.53
Illness duration	0.19	0	1.41	3.54	0.23	0	1.76	3.96

Note: Prop measures the proportion of the sample in each group.

Table 3
Estimation results.

Parameter description	Males						Females					
	Illness of type 1			Illness of type 2			Illness of type 1			Illness of type 2		
	$\boldsymbol{\Theta}$	$\hat{\boldsymbol{\Theta}}$	*ASE*	$\boldsymbol{\Theta}$	$\hat{\boldsymbol{\Theta}}$	*ASE*	$\boldsymbol{\Theta}$	$\hat{\boldsymbol{\Theta}}$	*ASE*	$\boldsymbol{\Theta}$	$\hat{\boldsymbol{\Theta}}$	*ASE*
Utility function												
Utility of being sick	α_{01}	−3177.744	11.923	α_{02}	−349.000	391.191	α_{01}	−2365.095	61.993	α_{02}	−1659.764	888.334
Utility of seeking treatment	α_{11}	−89.329	5.289	α_{12}	−67.935	23.508	α_{11}	−63.310	25.289	α_{12}	−8.482	2.803
Utility of missing work	α_{21}	−128.511	5.099	α_{22}	−153.783	163.874	α_{21}	−86.547	33.489	α_{22}	−1.948	1.843
Marginal utility of cons	α_{31}	0.156	0.014	α_{32}	0.582	0.703	α_{31}	0.054	0.024	α_{32}	0.528	0.513
Recovery probability												
Constant	η_{01}	−2.969	0.116	η_{02}	−6.881	5.373	η_{01}	−2.828	0.198	η_{02}	−0.523	0.373
Coeff on v_{t+1}	η_{11}	0.004	0.000	η_{12}	−0.247	0.423	η_{11}	0.004	0.004	η_{12}	0.005	0.005
Coeff on v_{t+1}^2	η_{21}	−0.000	0.000	η_{22}	0.076	0.092	η_{21}	−0.000	0.000	η_{22}	−0.007	0.007
Coeff on a_{t+1}	η_{31}	0.007	0.000	η_{32}	−2.651	1.073	η_{31}	0.006	0.006	η_{32}	0.184	0.129
Coeff on a_{t+1}^2	η_{41}	0.001	0.000	η_{42}	1.757	1.632	η_{41}	0.001	0.001	η_{42}	0.012	0.021
Coeff on $v_{t+1}a_{t+1}$	η_{51}	0.000	0.000	η_{52}	0.068	0.010	η_{51}	0.000	0.000	η_{52}	0.001	0.002
Coeff on t	η_{61}	0.572	0.024	η_{62}	0.531	0.241	η_{61}	0.398	0.075	η_{62}	0.230	0.141
Coeff on t^2	η_{71}	−0.075	0.002	η_{72}	−0.049	0.039	η_{71}	−0.042	0.008	η_{72}	−0.001	0.004
Coeff on t^3	η_{81}	0.003	0.000	η_{82}	0.001	0.001	η_{81}	0.002	0.000	η_{82}	0.001	0.001
Coeff on good health	η_{91}	−0.050	0.030	η_{92}	−0.306	0.754	η_{91}	−0.035	0.022	η_{92}	−0.014	0.008
Coeff on fair/poor health	$\eta_{10,1}$	−0.115	0.043	$\eta_{10,2}$	−0.026	0.098	$\eta_{10,1}$	−0.035	0.029	$\eta_{10,2}$	0.043	0.031
Coeff on 45–64 yrs of age	$\eta_{11,1}$	−0.019	0.026	$\eta_{11,2}$	−0.284	0.339	$\eta_{11,1}$	−0.003	0.019	$\eta_{11,2}$	0.008	0.010
Illness probability												
Constant	δ_{01}	−6.660	0.109	δ_{02}	−17.677	4.094	δ_{01}	−6.465	1.109	δ_{02}	−8.984	0.562
Coeff on good health	δ_{11}	0.034	0.098	δ_{12}	4.731	3.884	δ_{11}	−0.035	0.109	δ_{12}	0.161	0.652
Coeff on fair/poor health	δ_{21}	−0.174	0.171	δ_{22}	−0.135	0.297	δ_{21}	0.022	0.032	δ_{22}	0.190	1.003
Coeff on 45–64 yrs of age	δ_{31}	−0.457	0.099	δ_{32}	−0.372	0.127	δ_{31}	−0.392	0.107	δ_{32}	−0.744	0.872
Replacement rate												
Constant	ϕ_1	5.649	2.681				ϕ_1	6.183	5.559			
Coeff on a_{t+1}	ϕ_2	−1.758	0.863				ϕ_2	−1.438	1.782			
Proportion facing 0% OOP												
Constant	θ_{10}	−0.630	0.280				θ_{10}	−0.471	0.239			
Coeff on good health	θ_{11}	−0.031	0.333				θ_{11}	−0.198	0.291			
Coeff on fair/poor health	θ_{12}	0.193	0.485				θ_{12}	0.251	0.426			
Proportion facing 20% OOP												
Constant	θ_{20}	−0.529	0.282				θ_{20}	−0.738	0.255			
Coeff on good health	θ_{21}	−0.222	0.341				θ_{21}	−0.027	0.310			
Coeff on fair/poor health	θ_{22}	1.331	0.649				θ_{22}	0.164	0.464			

Note: $\boldsymbol{\Theta} \equiv$ parameter, $\hat{\boldsymbol{\Theta}} \equiv$ parameter estimate, ASE $\equiv$ asymptotic standard error. $\ln \mathcal{L}(\boldsymbol{\Theta}, \boldsymbol{\theta}) = -11608.671$ (males), $\ln \mathcal{L}(\boldsymbol{\Theta}, \boldsymbol{\theta}) = -12887.577$ (females).

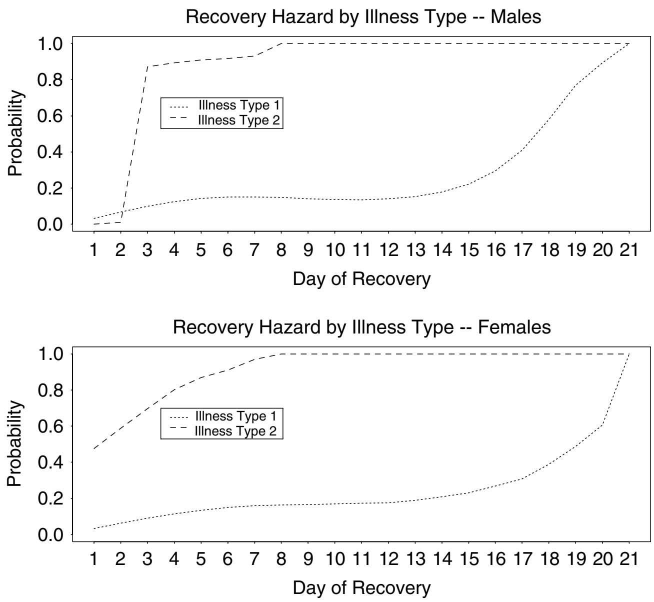

Fig. 1. Recovery hazard—unconditional on absence and treatment history.

status is good or fair/poor. The baseline age is 25–44 years with a dummy indicating 45–64 years of age.

Table 3 displays the estimates and asymptotic standard errors of the utility function parameters, the recovery and illness probability parameters, and the budget constraint parameters. Because the constant in the contemporaneous utility while well is normalized to zero, the negative constants in the utility while sick indicate that illnesses (of either type) create disutility for men and women.[16] Furthermore, illnesses of type 1 are almost ten times worse (unconditional on behavior) than illnesses of type 2 among men.[17] The disutility of physician visits, that both genders experience, may represent the distaste or discomfort of treatment, measured in dollars, as well as the costs of traveling and waiting time. Missing work while sick reduces current period utility for men and women indicating that absence, while perhaps income costly and recovery beneficial, imposes additional costs captured by preferences. The marginal utility of consumption while well is normalized to one for both males and females; the estimates suggest that an additional dollar of income provides less utility when sick than when well for both genders and both types of illness.

Fig. 1 depicts the recovery hazards for men and women unconditional on absenteeism and medical care use during the episode, and conditional on the discrete illness types.[18] For both genders, the unobserved illness distribution reveals that one type of acute illness lasts only a few days with rates of recovery near 90% by day three for men and closer to one week for women. The other illness is likely to last two weeks or more in duration. The productive effect of absences and doctor visits, relative to time, is quite small for some illnesses but more substantial for others. Absences are more productive than medical care, raising recovery probabilities by up to three percent (of the non-absent recovery probability), except for illnesses of type 2 among men which require multiple days out of work to produce an increase in the probability of recovery. One doctor visit generally increases the probability of recovery (by less than one percent of the untreated probability of recovery), but two or more visits are necessary to increase the recovery probability for males contracting type 2 illnesses. Missing work and seeking treatment are complements for men and women (regardless of illness type), but the multiplicative effect is quite small. The coefficients on health status indicate that men and women in poorer health are slower to recover from illness. Age does not have a significant impact on recovery.

The absence-dependent wage replacement rate, or percent of the wage that is replaced by sick leave coverage, captures the fact that the stock of absence days is not limitless. The estimated coefficients indicate that the replacement rate is 98.0% for the first absence of an illness episode among males. The next absence results in only 89.4% of the daily wage being replaced. Sick leave coverage would replace 59.3% of the daily wage for a third absence. For females, the figures are 99.1%, 96.5%, and 86.6%. It also accounts for other (long-run) costs associated with missing work, even though the employer offers sick leave coverage. Such costs may include depletion of the stock of sick leave days, increased work load upon returning to work, and employer dissatisfaction with employee absences. Individuals with the same lengths of episode-specific durations of absence (and the same duration of sickness) are observed to make different absenteeism choices that cannot depend on differences in preferences or recovery outcomes (which are similar at that point). Differences in these choices across those with and without sick leave identify the effect of wage replacement (which depends on accumulated absences). The estimated replacement rates seem to suggest gender differences in the generosity of sick leave coverage; however, because data on actual replacement rates are not available, these estimated values also capture other negative effects of multiple absences within an episode.[19]

Finally, while the out-of-pocket financial responsibility rate is known for some individuals in the sample (i.e., those who sought treatment), it must be estimated for others. The results indicate that about 27% of individuals face zero responsibility for physician visit charges. About 50% of individuals are responsible for the entire charge. Although this finding appears much higher than national estimates of the population percentage who are uninsured in 1987, one must consider exactly what this estimate measures. In particular, it is the average proportion paid out of pocket over an illness spell among insured individuals. Recall, if an insured individual's medical care costs fall below his deductible (i.e., a frequent occurrence for the first visit in an insurance year), he pays the full cost of visiting a physician.

The parameters measuring rates of illness (i.e., acute illness contraction probabilities) suggest that shorter term illnesses are more likely for individuals of each gender, health status, and age than longer term illnesses. The daily illness contraction and

16 While the relative importance of preferences, economic variables, and recovery from and contraction of illness can be evaluated for males and females independently, the values of the estimated parameters of a man's maximization problem cannot be directly compared to those of a women's problem. That is, the model parameters associated with each gender's problem are not estimated jointly.

17 The coefficient estimates suggest that individuals may be willing to pay hundreds, or even thousands, of dollars to recover immediately from these illnesses. After discussing all of the estimated primitives of the model, I consider reasons why these estimates of the disutility of sickness may be too large.

18 The distribution of unobserved illness types is not jointly estimated across genders and, hence, the estimated illness types are not comparable. An attempt was made to estimate gender-neutral illness types, but a better fit was obtained by allowing gender-specific unobserved illness types. Also, attempts to add more points of support to the discrete approximation of unobserved illness heterogeneity did not improve the fit of the model significantly.

19 The only mechanism in the model by which jobs of males differ from jobs of females is wage (assumed exogenous) and the replacement rate. It would be interesting to explore differences in the costs of missing work by occupation or job tasks. This avenue is potentially picked up through the estimated wage replacement rates for those with sick leave coverage. Evidence from Barmby et al. (2002) suggests that differences in absence rates among men and women can be attributed to differences in hours of work (among other things), but there are no differences in observed replacement rates in their data since the benefit is universally applied.

recovery probabilities and the behavioral probabilities associated with absence and treatment translate into an 80% chance, for men, of not being observed to have an illness episode (of the kind sampled) over the entire year. For women, this probability is 58%. These figures reflect that females are more likely than males to suffer an acute illness for which they chose to miss work or seek treatment.

5.2. The fit of the model

I statistically assess the ability of the model to capture behavior during an episode of illness by comparing the observed frequencies and predicted probabilities of missing work and seeking medical treatment, the observed and predicted recovery hazard rates, and several other dimensions of interest. In most cases the hypothesis that the observed proportions and the predicted probabilities come from the same population probability distribution is not rejected at conventional significance levels using the Andrews's (1988) corrected chi-square test. Graphical representations of the model's fit (Figs. 2 and 3) reveal that the model does extremely well in capturing behavior over the illness episode. For both men and women, the model overpredicts the recovery hazard during the third week of an illness, which is likely attributed to the small number of individuals with illness episodes lasting this long. The model underpredicts treatment probabilities for females, but fits the total number of visits well. Absences are similarly underpredicted for females.

5.3. Discussion

Given the pecuniary costs of absence and treatment (both in preferences and in the budget constraint), one may wonder why anyone in this model would stay home from work or go to the doctor if the positive impact of these behaviors on recovery is so small. While the impacts of absence and treatment on recovery appear small, one must compare the value of being well (a stationary, life-time construct in the model that incorporates the uncertainty of future sickness) with the value of getting or being sick (which incorporates the uncertain duration of sickness). The stationary well value is over twice as large as the value of sickness (on day one of an illness). Hence, even a one percent increase in the probability of recovery increases the value of that absence and treatment alternative by a significant amount.[20]

The estimated cost of being sick, however, may still appear implausibly high. One explanation for this finding is that the marginal effectiveness of absence and treatment may be biased downward due to endogeneity of the inputs. That is, something unobserved, such as severity of illness, may affect both the decision to be absent or seek treatment as well as the probability of recovery. The model attempts to control for this unobserved heterogeneity by including illness unobservables, whose distribution is estimated. In fact, the endogeneity of the inputs was explored more thoroughly by estimating a simple, static selection model implied by the structural model: the recovery probability is the main outcome equation of interest and the arguments of the choice or selection equation (i.e., the absence and treatment inputs) are dictated by the model's optimization structure. That is, the structure of the model suggests which observable variables are "instruments" or exclusion restrictions that should appear in the choice equation but not in the outcome equation and hence identify the marginal effects of the inputs. Variables that enter the utility function or the budget constraint only will affect the decision to miss work or seek treatment but not the recovery probability, conditional on the input decisions. These variables are income, sick leave coverage, price of medical care, health insurance coverage, and out-of-pocket responsibility.[21] While endogeneity bias is a legitimate concern when estimating the illness recovery hazard, conventional statistical methods to correct for such bias do not appear sufficient. The structural method employed in this paper goes a step further in allowing unobservables to influence multiple outcomes of interest, as is evidenced by the differences in the estimated marginal effects of inputs on recovery from the estimated effects using simple static models.

Assuming that the estimated marginal effects of absence and treatment do not suffer from additional endogeneity bias and that the positive impacts of absence and treatment are truly small, the model structure requires that the cost of illness be high in order to rationalize the observation that people do miss work and seek treatment for these illnesses. However, the model could also be misspecified in some way. It is possible that the model does not fully solve the endogeneity problem, and that the effects of work absences and doctor visits on the recovery probability are actually higher than the estimates imply. If this is the case, then the observed absence and treatment behavior could be rationalized using much lower (and perhaps more plausible) costs of illness. Alternatively, the assumption that individuals know the recovery technology may be inaccurate. Observed treatment behavior, for example, might be explained more appropriately by allowing individuals to have incorrect expectations of treatment effectiveness or by letting risk-averse individuals learn (through physician contact) what type of illness they have. Finally, the assumption of a stationary value of being well, and the implied requirement that contraction of an illness and behavior during the illness episode do not alter the observed description of the individual (i.e., he is observationally the same both before contraction and after recovery), may lead to a high estimated cost of being sick.

6. Policy experiments

Having obtained the structural parameters of a model describing an individual's optimal decisions regarding work absence and medical care use during an episode of illness, it is possible to introduce changes in the economic incentives that affect these decisions and to predict how an individual would respond. I conduct several policy experiments to assess the effects on behavior of changes in the constraints faced by employed individuals who get sick. The policy instruments in the data are sick leave coverage, health insurance coverage, out-of-pocket responsibility, and price of

20 For example, the value of being well ranges from 65,400 to 508,400 for males (and 23,600 to 316,000 for females) depending on income, health status, age, and sick leave and health insurance coverage. Sickness reduces daily utility by as much as 3000 dollar-valued utils (for some types of illnesses) each day of an illness. Hence, a one percent increase in the probability of recovery and returning to a state of wellness must be compared to the costs of being sick and the additional costs of absence and treatment once sick.

21 I estimate a two stage least squares regression (and calculate robust standard errors to account for correlated unobservables across individual episodes of illness), as well as an ordinary least squares regression treating the inputs as exogenous, in order to verify the appropriateness of these variables as exclusion restrictions and to examine the bias in the estimated input effects. First, the joint null hypothesis that the instruments are valid instruments (i.e., uncorrelated with the error term) and that the instruments are correctly excluded from the recovery equation cannot be rejected. Secondly, the marginal effects of the inputs (absence and treatment) are quite different in the two specifications. However, the estimated *negative* impact of (low levels of) treatment in the OLS model is only slightly mitigated when the endogeneity of treatment is accounted for. The preferred structural model estimated in this paper accounts for a potential source of endogeneity bias by specifically modeling unobserved differences in illness. It is this aspect of the model that allows us to uncover positive impacts of absence and treatment on illness recovery.

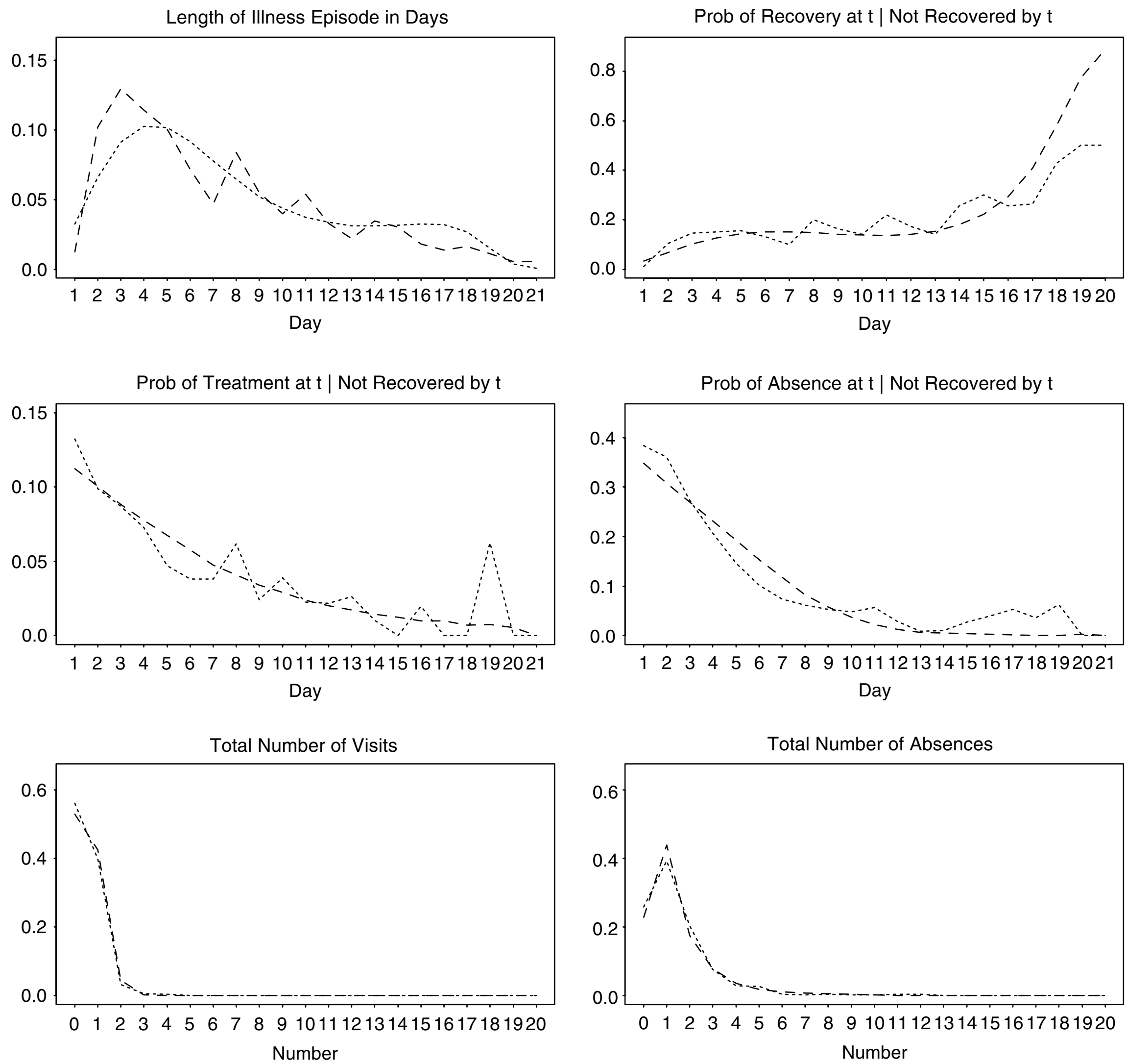

Fig. 2. Observed (· · ·) and predicted (– – –) behavior of males.

treatment. In particular, the goal of this work is to understand the different responses of men and women to economic incentives, in light of differences in preferences and health production capabilities. The baseline predicted behavior is displayed in Table 4.

6.1. *Policy alternatives involving one policy instrument*

Only one economic constraint is altered in each of the first three experiments. These include extending sick leave coverage to everyone (Experiment 1), eliminating sick leave coverage (Experiment 2), and providing full coverage of physician visits (Experiment 3). The results of these experiments for both genders are presented in Table 5.

As expected, universal sick leave provision (Experiment 1) increases the probability of having an absence and the number of absences, and reduces the probability of having a doctor visit and the number of visits. Interestingly, these responses are much larger for men than for women. The probability of zero absences falls by 21% with expected absences up almost 12% for men while the corresponding numbers for women are 7% and 5%. Perhaps females are less responsive to policies that extend sick leave coverage because, prior to the extension, they are less constrained by existing sick leave policy. This is not to suggest that they are more likely to have coverage but that they are more likely to be absent, regardless of coverage. The simulations reveal (not shown) that lower income men are more likely than upper income men to alter their absence behavior when sick leave coverage is provided (i.e., the probability of zero absences decreases by 24% and 16%, respectively). Although the amount of income replaced by sick leave coverage is higher at higher incomes, the behavior is not linear despite the constant marginal utility of current income. This is a result of the non-linearity of the value function and forward-looking decision making. Among both genders, those in better health have a larger percentage increase in absenteeism than those in worse health. This behavior reflects that recovery is more responsive to visits than absences at lower levels of health. For both men and women, this policy reduces the length of the illness episode slightly.

Eliminating sick leave coverage (Experiment 2) produces a greater behavioral response (than universal sick leave coverage) because the prevalence of such coverage is high at the baseline. We see that substitution of doctor visits for absences is greatest among those with higher incomes. Their ability to make this substitution is related to the higher prevalence of health insurance coverage, the lower out-of-pocket responsibility, and larger incomes to finance medical care consumption. Upper income males engage in this substitution more so than upper income women. While higher

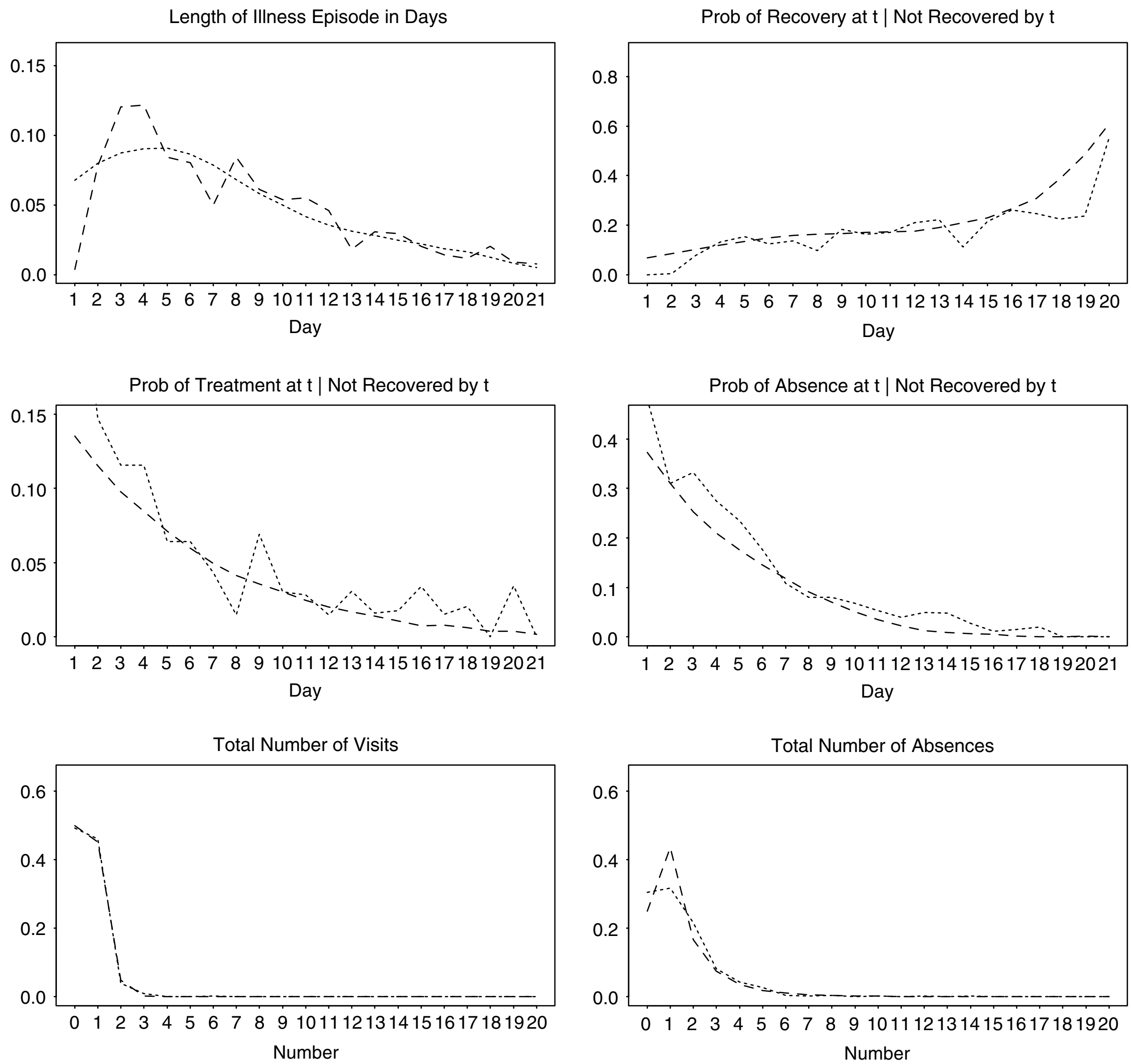

Fig. 3. Observed (· · ·) and predicted (– – –) behavior of females.

income individuals are less likely to be absent and more likely to be in jobs that offer sick leave coverage, this policy experiment demonstrates the importance of the sick leave benefit to these individuals.

Given the generosity of health insurance coverage in many European countries, it is interesting to simulate the behavioral responses of our US sample when health insurance is extended to all individuals (Experiment 3). When the coinsurance rate or percent paid out of pocket is set to zero for everyone and sick leave coverage is unchanged, physician visits per episode increase by 11% and 8% for men and women, respectively. Also, men are up to 18% less likely to miss work (among those originally facing 100% of medical care costs) when medical care is free and similar women are 9% less likely to be absent. Among men, those with sick leave coverage consume relatively more physician visits than men who do not have sick leave coverage; among women, differences in behavior by sick leave are less apparent. Despite the disutility of treatment and the short duration and minimal reliance on medical care of type 2 illnesses at baseline, men with these illnesses are much more likely to seek treatment under universal insurance coverage because the marginal effect of treatment on recovery from type 2 illnesses becomes positive after several visits. A similar response occurs among women, but for different reasons. The utility costs of visits are relatively low and the marginal impact of treatment is positive (when accompanied by an absence) for women with type 2 illnesses. Overall, illness duration falls when medical care is free, but the differences are negligible.[22]

6.2. *Policy changes involving combinations of policy instruments*

Policies that alter both sick leave and health insurance coverage are likely to result in different behavioral responses than changes in one policy instrument in isolation. Such combinations might be desired because, for example, providing full coverage of physician visits but allowing no change in sick leave policy does not address

22 A back of the envelope cost/benefit analysis suggests that the expected costs of fully covering doctor visits for acute illnesses is $20.28 per episode for males and $20.84 per episode for females. The per-episode benefits to the firm of increased productivity (valued at the worker's wage) plus the reduced wage replacement costs associated with the reduced absenteeism is $4.49 for males and $1.54 for females. To this benefit we should add the individual welfare gain that captures reductions in illness duration offset by costs of absence and treatment. This can be measured by differences in the stationary value of being well or by the expected value of contracting an illness (i.e., the expected value of sickness on day one of an illness). Differences in these (lifetime) value functions are negligible across experiments.

Table 4
Predicted absence and treatment behavior—baseline.

Characteristic	$p(a=0)$	$E(a)$	$E(a\|a>0)$	$p(v=0)$	$E(v)$	$E(v\|v>0)$	$E(T)$
Male observed behavior	0.26	1.41	1.90	0.56	0.49	1.13	7.35
Male predicted behavior	0.23	1.45	1.88	0.53	0.52	1.10	7.93
By sick leave							
Available	0.18	1.57	1.92	0.56	0.49	1.11	7.84
Not available	0.35	1.13	1.74	0.45	0.60	1.10	8.16
By health insurance							
Insured 0% OOP	0.25	1.42	1.89	0.48	0.58	1.12	7.92
Insured 20% OOP	0.24	1.44	1.90	0.50	0.56	1.12	7.93
Insured 100% OOP	0.21	1.46	1.86	0.56	0.47	1.09	7.93
Uninsured 100% OOP	0.21	1.46	1.85	0.57	0.47	1.09	7.95
By illness type							
Type 1	0.23	1.45	1.88	0.53	0.52	1.10	7.94
Type 2	0.00	2.99	2.99	0.96	0.04	1.02	3.13
Female observed behavior	0.30	1.42	2.04	0.49	0.57	1.12	7.79
Female predicted behavior	0.25	1.39	1.85	0.50	0.55	1.10	7.45
By sick leave							
Available	0.23	1.47	1.91	0.51	0.54	1.11	7.41
Not available	0.29	1.22	1.72	0.47	0.58	1.10	7.53
By health insurance							
Insured 0% OOP	0.26	1.37	1.85	0.46	0.60	1.11	7.45
Insured 20% OOP	0.26	1.38	1.86	0.48	0.58	1.11	7.43
Insured 100% OOP	0.24	1.41	1.86	0.53	0.52	1.10	7.46
Uninsured 100% OOP	0.24	1.40	1.84	0.53	0.52	1.10	7.45
By illness type							
Type 1	0.27	1.36	1.86	0.48	0.58	1.11	7.93
Type 2	0.00	1.82	1.82	0.73	0.29	1.09	1.82

Note: All probabilities are conditional on having an episode of illness. $p(a)$, $p(v)$: Probability of zero absences (visits). $E(a)$, $E(v)$: Average # of absences (visits) ≥ 0 per episode. $E(a|a>0)$, $E(v|v>0)$: Average # of absences (visits), conditional on any, per episode. $E(T)$: Average duration of episode.

Table 5
Percentage change in predicted absence and treatment behavior under policy experiments 1–3.

Characteristic	Experiment 1				Experiment 2				Experiment 3			
	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$
Male behavior	−21.10	11.78	5.66	−5.89	76.39	−33.06	−21.35	22.80	9.47	−1.70	−8.75	11.50
By sick leave												
Available	0.01	0.00	−0.01	0.01	135.86	−43.69	−28.83	34.51	10.24	−1.21	−8.28	12.21
Not available	−50.05	52.34	24.31	−18.71	−0.01	0.01	0.02	−0.02	7.67	−2.94	−9.97	9.70
By health insurance												
Insured 0% OOP	−20.07	12.28	6.19	−5.23	73.03	−34.37	−23.00	20.40	0.43	−0.21	−0.13	0.11
Insured 20% OOP	−21.20	11.94	5.69	−5.24	74.11	−33.94	−21.88	20.96	3.36	−0.73	−3.17	3.77
Insured 100% OOP	−21.60	11.45	5.40	−6.63	79.66	−31.95	−20.40	25.24	18.25	−2.88	−14.83	22.78
Uninsured 100% OOP	−21.55	11.25	5.21	−6.46	81.06	−32.58	−20.91	26.54	18.00	−3.16	−14.64	22.76
By illness type												
Type 1	−21.10	11.79	5.67	−5.90	76.39	−33.14	−21.40	22.81	9.47	−1.71	−8.76	11.51
Type 2	0.00	0.00	0.00	0.03	0.00	0.00	0.00	−0.11	0.00	0.00	−2.47	66.03
Female behavior	−7.12	4.96	2.23	−2.08	20.97	−14.89	−6.22	5.87	4.79	−1.15	−7.22	8.26
By sick leave												
Available	0.00	0.00	0.00	0.00	32.99	−20.47	−8.85	8.69	4.94	−1.03	−7.11	8.44
Not available	−19.80	18.57	7.61	−6.51	0.00	0.00	0.00	−0.01	4.44	−1.42	−7.47	7.84
By health insurance												
Insured 0% OOP	−6.69	4.89	2.19	−1.77	20.69	−15.00	−6.47	5.33	0.03	−0.03	−0.01	0.01
Insured 20% OOP	−6.91	4.94	1.92	−1.62	20.04	−14.68	−5.87	4.96	1.76	−0.48	−3.12	3.31
Insured 100% OOP	−7.49	5.03	2.40	−2.55	21.54	−14.93	−6.23	6.66	9.15	−2.04	−12.40	16.07
Uninsured 100% OOP	−7.01	4.82	2.02	−2.28	23.20	−15.30	−6.10	6.40	9.50	−2.10	−12.76	16.23
By illness type												
Type 1	−7.12	5.52	2.52	−2.17	20.98	−16.61	−7.04	6.14	4.79	−1.28	−5.19	5.70
Type 2	0.00	0.00	−0.01	0.05	0.00	−0.02	0.02	−0.07	0.00	0.01	−22.70	67.22

Exp. 1: % Out of Pocket unchanged, Sick leave covered. Exp. 2: % Out of Pocket unchanged, Sick leave not covered. Exp. 3: 0% Out of Pocket, Sick leave unchanged. All probabilities are conditional on having an episode of illness. $p(a)$, $p(v)$: Probability of zero absences (visits). $E(a)$, $E(v)$: Average # of absences (visits) ≥ 0 per episode.

the costs associated with missing work in order to consume the free medical services for those individuals who do not have sick leave coverage. Because sick leave coverage is more prevalent among high wage jobs than among low wage jobs, the work-loss costs would be disproportionately borne by lower income individuals if sick leave coverage is unchanged. Table 6 displays the behavioral responses to policies that provide full sick leave coverage and full health insurance coverage (Experiment 4), no sick leave coverage and full health insurance coverage (Experiment 5), and no sick leave coverage and no health insurance coverage (Experiment 6).

When sick leave and health insurance are both fully provided (Experiment 4) the total number of absences and visits increase for both men and women (by between 4% and 11% on average). There is a greater percentage change in absence behavior (relative to medical care consumption) among men and the opposite behavioral response among women. The changes in behavior are quite different between those who previously held sick leave coverage and those who did not. As expected, among men who had such coverage, their response changes are dominated by increased medical care visits (up 12%) with very little change in absence behavior. Among those who did not have sick leave coverage there is a

Table 6
Percentage change in predicted absence and treatment behavior under policy experiments 4–6.

Characteristic	Experiment 4				Experiment 5				Experiment 6			
	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$
Male behavior	−13.07	10.59	−3.00	5.57	89.53	−35.69	−29.77	33.89	65.63	−30.90	−14.53	13.81
By sick leave												
Available	10.24	−1.22	−8.28	12.21	153.04	−46.25	−36.72	46.17	122.25	−41.65	−22.45	25.06
Not available	−45.01	51.14	14.30	−8.87	7.68	−2.95	−9.97	9.70	−6.76	2.54	8.17	−7.86
By health Insurance												
Insured 0% OOP	−20.05	12.25	6.19	−5.23	73.73	−34.71	−23.23	20.60	51.75	−29.94	−6.50	2.50
Insured 20% OOP	−18.56	11.55	2.43	−1.33	78.57	−35.01	−24.96	24.64	56.44	−30.26	−9.26	6.07
Insured 100% OOP	−5.76	9.30	−9.31	16.06	104.90	−36.45	−34.61	47.11	78.95	−31.65	−20.22	25.01
Uninsured 100% OOP	−6.90	9.17	−9.23	16.16	107.11	−37.23	−34.96	48.46	80.35	−32.28	−20.73	26.33
By illness type												
Type 1	−13.07	10.59	−3.01	5.56	89.53	−35.77	−29.82	33.88	65.63	−31.00	−14.56	13.83
Type 2	0.00	0.00	−2.47	66.08	0.00	0.00	−2.47	65.86	0.00	0.00	1.85	−49.18
Female behavior	−2.63	3.87	−4.99	6.17	26.45	−16.17	−13.38	14.04	16.50	−13.84	−0.36	−0.77
By sick Leave												
Available	4.94	−1.03	−7.11	8.44	39.07	−21.70	−15.88	17.01	28.05	−19.44	−3.09	1.94
Not available	−16.09	17.29	0.10	1.35	4.44	−1.42	−7.47	7.84	−3.66	1.15	6.10	−6.40
By health insurance												
Insured 0% OOP	−6.68	4.88	2.18	−1.77	20.70	−15.01	−6.47	5.33	11.59	−12.75	7.31	−8.30
Insured 20% OOP	−5.23	4.47	−1.19	1.64	22.04	−15.17	−8.97	8.19	12.25	−12.72	4.80	−5.87
Insured 100% OOP	1.13	3.04	−10.03	13.54	32.10	−17.24	−18.57	22.59	21.52	−14.92	−6.23	6.66
Uninsured 100% OOP	1.51	3.01	−10.56	13.81	33.34	−17.55	−18.13	22.05	23.18	−15.28	−6.10	6.39
By illness type												
Type 1	−2.62	4.29	−2.67	3.52	26.46	−18.04	−12.15	11.74	16.50	−15.42	−2.82	1.51
Type 2	0.00	0.01	−22.72	67.30	0.00	−0.01	−22.68	67.12	0.00	−0.03	18.45	−53.58

Exp. 4: 0% Out of Pocket, Sick leave covered. Exp. 5: 0% Out of Pocket, Sick leave not covered. Exp. 6: 100% Out of Pocket, Sick leave not covered. All probabilities are conditional on having an episode of illness. $p(a)$, $p(v)$: probability of zero absences (visits). $E(a)$, $E(v)$: average # of absences (visits) ≥ 0 per episode.

large increase in absences (up 51%) and the total number of physician visits actually falls (almost 9%). Previously insured men also engage in more work absence and less medical care consumption under this policy change. The behavior reflects the complementarity between absences and visits in the recovery probability (on one hand), but also the relatively greater effectiveness of absences over visits (on the other hand). It also emphasizes the costliness of absences and visits even when this behavior is fully (financially) covered by sick leave and health insurance. Women with sick leave coverage respond similarly to men, but those without sick leave coverage have more absences (up 17%) and slightly *more* visits relative to their previous behavior. This policy also reduces the episode duration of some men by over 4%.

Again driven by the large percentage of individuals who were previously reimbursed for illness-related absences, providing full health insurance coverage but eliminating sick leave coverage (Experiment 5) results in more medical care use and less work absence overall, and among all subgroups, for both men and women. The responses of men, however, are much more dramatic than those of women. This policy also has a large effect on illness duration among men, increasing episode lengths by an average of 4%. The duration of illness among upper income males is over 7% longer given the large decrease in absenteeism (which is generally more effective than medical care in restoring health among these illnesses). Illness episodes are not significantly different for women under this policy change.

The last combination of changes in policy instruments involves eliminating both sick leave and health insurance coverage (Experiment 6). Illness durations of men and women are similarly affected by this policy change as by the change in Experiment 5. However, their work absence and medical care consumption behavior is quite different. In general, men respond by reducing absenteeism (by 30%) but increasing medical care consumption (by almost 14%). Women, on the other hand, reduce absenteeism (by almost 14%) and alter their medical care consumption very little. As expected, upper income individuals are more likely to replace the reduction in work absence with medical care. This substitution is much greater among upper income men than among similar women. The substitution is also greater among less healthy men than among similar women. Experiments 5 and 6 demonstrate that regardless of health insurance coverage, elimination of sick leave coverage greatly increases the consumption of medical care (at least among men).

6.3. *Policy alternatives involving new policy instruments*

The policy experiments discussed above involve changing sick leave or health insurance characteristics in ways that appear in the data. That is, the data contain observations on individuals who have and do not have sick leave coverage and who have and do not have health insurance (and varying degrees of responsibility). Estimation of an approximation to the value functions or of a reduced-form model of absence and treatment behavior would allow for simulation of the effects of the policy changes considered in the previous experiments.[23]

One advantage of the behavioral model (i.e., solution and estimation of the individual's optimization problem) is that it allows for the introduction of several policies that we do not observe in the data. Because the individual's preferences, constraints, and illness transitions are explicitly modeled, policies that alter these constraints and the subsequent consumption of absence and treatment can be introduced and the problem solved again. Policy alternatives that introduce new policy instruments and therefore require solution of the individual's optimizing behavior include requiring at least one physician visit for coverage of absence days (Experiment 7), restricting access to medical care during the first three days of an illness episode (Experiment 8), and allowing the price of physician visits to be a function of behavior. For comparisons, I simulate an across-the-board increase in visit prices (Experiment 9). Then I simulate a penalty for delaying treatment by allowing the price of care to depend on the number of elapsed

23 Gilleskie (1998) demonstrates that reduced-form models replicate the averages observed in the data very well, but do not capture the range of predictions to the extent of the behavioral model. It is also shown that the reduced-form models can predict unexpected behavior (on average) when alternative policies such as those described above are introduced.

Table 7
Percentage change in predicted absence and treatment behavior under policy experiments 7–8.

Characteristic	Experiment 7				Experiment 8			
	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$
Male behavior	47.68	−18.52	−33.97	38.68	−27.27	−6.08	32.17	−38.22
By sick leave								
Available	93.97	−29.23	−40.93	51.67	−33.11	−5.05	31.72	−42.11
Not available	−13.14	16.28	−14.22	13.12	−29.22	−0.89	40.11	−34.85
By health insurance								
Insured 0% OOP	43.60	−18.17	−37.35	36.29	−25.70	−6.30	37.06	−37.38
Insured 20% OOP	43.51	−18.07	−34.64	35.11	−26.64	−6.40	35.37	−38.01
Insured 100% OOP	52.33	−18.84	−32.17	42.03	−28.58	−5.83	28.76	−38.94
Uninsured 100% OOP	54.39	−19.96	−33.00	44.31	−27.88	−6.41	27.95	−38.83
By illness type								
Type 1	47.68	−18.58	−33.89	38.54	−27.27	−6.11	32.23	−38.22
Type 2	0.00	0.01	−74.79	198.02	0.00	0.00	3.63	−95.40
Female behavior	14.09	−9.00	−19.41	19.14	−30.11	−3.30	38.56	−40.53
By sick Leave								
Available	24.67	−14.29	−22.51	22.94	−30.33	−4.47	37.91	−41.49
Not available	−4.48	5.27	−12.19	11.28	−30.67	0.81	40.60	−38.89
By health insurance								
Insured 0% OOP	13.25	−8.63	−19.38	17.09	−29.38	−3.05	45.87	−42.01
Insured 20% OOP	12.98	−8.65	−19.27	17.69	−30.06	−2.83	41.97	−40.77
Insured 100% OOP	15.11	−9.33	−19.48	21.18	−30.41	−3.65	33.57	−39.39
Uninsured 100% OOP	16.10	−9.72	−19.31	21.00	−31.38	−3.51	34.19	−40.61
By illness type								
Type 1	14.09	−10.05	−12.29	11.37	−30.10	−3.69	39.13	−38.20
Type 2	0.00	0.02	−73.84	199.02	0.00	−0.01	34.35	−94.56

Exp. 7: Absence reimbursed only if $v \geq 1$. Exp. 8: Prohibit physician visit in first 3 days of illness.

sick days without treatment (Experiment 10). Finally, I simulate a subsidy for sicker patients (indicated by more doctor visits) by allowing the visit price to be a decreasing function of the number of visits (Experiment 11).

Although some individual sick leave policies in the US require a physician visit for reimbursement, this requirement is not uniform, nor is this information available in the NMES data. In contrast, many European countries that offer generous sick leave coverage require that workers verify an illness-related work absence with physician certification. When a universal sick leave policy that requires physician verification of illness is introduced (Experiment 7), Table 7 reveals that the probability of a physician visit increases as does the total number of such visits. Interestingly, absenteeism falls in general. The direction of the behavioral responses of men and women are similar but the percentage changes among men are about double that of women. The lower absence rate is clearly evident among those who previously had sick leave coverage as wage reimbursement now requires a doctor's visit. This requirement increases the number of visits and absences for those who previously did not have sick leave coverage regardless of treatment. As expected, those with higher incomes increase their consumption of visits relatively more than those with lower incomes. The reduction in absences is also greater for higher income individuals. While lengths of illness are about 2% longer under this policy, it is interesting to note that this is the only policy performed that produces significant changes in illness lengths in *opposite* directions for different subgroups. That is, men who previously held sick leave coverage find their illness episodes 3.3% longer while those who did not have sick leave coverage are well 1.3% sooner. The differences are similar, but smaller, for women.

In experiment 8, access to physician care is restricted during the first three days of an illness. This experiment attempts to uncover the effects of queues or treatment delays often claimed to be associated with nationalized health care provision. While some evidence of such queuing has been found among specialized procedures in Canada, for example, it is not unreasonable to simulate this experiment for less serious illnesses in order to measure responses. As expected, there is about a 40% reduction in medical treatment among both men and women. Males and females generally reduce the total number of absences, but the probability of any absence is almost 30% higher for both men and women. Individuals respond to this policy by increasing the likelihood of one absence, but reduce total consumption of both visits and absences. Because the probability of recovery within a short amount of time is fairly high (see Fig. 1), the benefit of medical treatment after day three of an illness is quite small. While total absences are fewer in general, those in relatively worse health continue to rely on recuperation at home (i.e., work absence) as is demonstrated by no change in total absence behavior among these men and a slight increase in the total number of absences among these women. Under this policy, individuals have illness episodes that are over 7% longer. The substantial disutility of illness suggests that this policy is not utility enhancing despite reductions in medical care expenses and income loss.

Finally, the price of medical care is also a policy instrument that can be manipulated. In the following experiments, I alter the physician visit price structure but keep health insurance and sick leave coverage unchanged. To allow for comparisons, a price change that could be simulated in reduced-form models is first discussed. As seen in Table 8, increasing physician visit prices by 50% (Experiment 9) results in more absences and fewer visits with a greater percentage reduction in the total number of visits per episode among men (down 10%) than among women (down 6%). This policy change also increases episode lengths significantly.

The next two experiments would not be feasible without estimating the structural parameters of an individual's dynamic decision making behavior because the policy changes are not observed in the data. Although difficult to introduce in practice because the date of illness contraction is often private information, I simulate the effects of a policy that defines the price of medical care to be an increasing function of the number of days that an individual is sick without seeking care (Experiment 10). As expected, this policy discourages consumption of medical care and encourages dependence on absences for recovery. This behavior is driven by the fact that the illnesses, in general, respond more to absence (in the recovery technology) and that treatment is effective only after multiple visits (for some illnesses). The extent of the changes in behavior, however, is less dramatic than an across-the-board increase in prices. A more realistic policy change regarding prices and one that allows for behavioral incentives is

Table 8
Percentage change in predicted absence and treatment behavior under policy experiments 9–11.

Characteristic	Experiment 9				Experiment 10				Experiment 11			
	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$
Male behavior	−9.47	1.87	8.38	−10.26	−4.41	0.97	3.85	−4.05	0.06	0.01	−0.09	0.25
By sick leave												
Available	−9.76	1.33	7.74	−10.66	−4.31	0.67	3.47	−4.11	0.07	0.00	−0.09	0.27
Not available	−8.46	3.31	10.14	−9.14	−4.25	1.81	4.96	−3.79	0.03	0.02	−0.07	0.18
By health insurance												
Insured 0% OOP	−0.39	0.20	0.12	−0.11	−0.19	0.10	0.06	−0.05	0.00	0.00	0.00	0.00
Insured 20% OOP	−3.31	0.58	3.32	−3.99	−1.46	0.35	1.39	−1.30	0.00	0.02	−0.02	0.09
Insured 100% OOP	−18.32	3.32	14.14	−20.06	−8.57	1.72	6.54	−8.03	0.12	0.01	−0.15	0.47
Uninsured 100% OOP	−17.09	2.76	13.40	−19.41	−8.08	1.52	6.33	−7.92	0.18	0.03	−0.19	0.50
By illness type												
Type 1	−9.47	1.86	8.39	−10.26	−4.41	0.97	3.86	−4.05	0.06	0.00	−0.09	0.24
Type 2	0.00	0.00	0.90	−23.52	0.00	0.00	0.26	−6.66	0.00	0.00	0.00	0.05
Female behavior	−5.06	1.23	5.62	−6.12	−2.02	0.54	2.07	−1.92	0.01	0.00	−0.06	0.13
By sick leave												
Available	−5.30	1.11	5.56	−6.33	−2.10	0.49	2.03	−1.97	0.01	0.00	−0.07	0.13
Not available	−4.58	1.50	5.77	−5.68	−1.89	0.62	2.18	−1.83	0.02	−0.01	−0.04	0.11
By health insurance												
Insured 0% OOP	−0.02	0.02	0.00	0.00	−0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Insured 20% OOP	−1.81	0.42	3.14	−3.25	−0.80	0.24	0.94	−0.80	0.00	0.00	−0.01	0.05
Insured 100% OOP	−9.75	2.26	9.41	−11.53	−3.90	0.97	3.57	−3.75	0.03	−0.01	−0.11	0.26
Uninsured 100% OOP	−8.89	1.95	9.28	−11.58	−3.55	0.81	3.48	−3.72	0.07	0.00	−0.10	0.26
By illness type												
Type 1	−5.06	1.36	5.15	−5.30	−2.03	0.60	2.17	−1.86	0.01	0.00	−0.06	0.12
Type 2	0.00	0.00	9.26	−25.00	0.00	0.00	1.33	−3.42	0.00	0.00	−0.07	0.36

Exp. 9: Physician visit price increased 50%. Exp. 10: Visit price is increasing in days ill without a visit. Exp. 11: Visit price is decreasing in the number of visits. All probabilities are conditional on having an episode of illness. $p(a)$, $p(v)$: Probability of zero absences (visits) $E(a)$, $E(v)$: Average # of absences (visits) ≥ 0 per episode.

to let the price of treatment be decreasing in the number of visits (Experiment 11). This has the potential to reduce the financial burden on those who need medical care the most. Unexpectedly, this experiment had little effect on absence or treatment behavior. One reason is likely to be the small number of treatment visits per episode; very few individuals have more than one physician visit during an illness episode since treatment is relatively less effective than absence or time.

7. Conclusion

This paper focuses on the changes in absence and treatment behavior of men and women under different policy alternatives regarding sick leave and health insurance coverage. To predict such behavior, I develop and estimate a dynamic stochastic structural model of a worker's absenteeism and medical care utilization during an episode of acute illness. This behavioral framework allows for predictions of the daily probability of illness and the probabilities of missing work, seeking treatment, and recovering on each day of the illness episode. Changes in the constraints faced by individuals produces changes in their predicted behavior.

Policy simulations based on the estimated empirical model reveal substantial responses to changes in economic incentives. The impacts of changes in sick leave and health insurance coverage on absenteeism, medical care use, and illness duration operate through preferences, financial constraints, and the recovery technology. In general, men appear to be more responsive than women to changes in these policy instruments. For example, a change from no sick leave coverage to provision of sick leave coverage produces a 45% increase in illness-related absences per episode among men, but only an 11% increase among women. Policies that provide free physician visits, as opposed to 100% financial responsibility by patients, induce men to increase consumption of medical care within an episode by 20% while women alter treatment behavior by only 15%. While women are less likely to have each of these coverage benefits, they appear to be less reliant on the services each offers. That is, reducing either of these benefits or broadening each of these benefits has little effect on the absence or medical care behavior of women during acute illnesses. Men, on the other hand, exhibit significant changes in behavior when these constraints are altered.

Most models of absenteeism fail to incorporate the voluntary decision of sick individuals to miss work, and these absences are the ones that are likely to be influenced by employer strategies to control absenteeism. The effect of sick leave coverage and of absenteeism itself can be captured by modeling daily absence decisions during an episode of illness. Most of the findings in the health care demand literature are based on analyses of medical care consumption data (i.e., counts or expenditures) that are aggregated over a year or over an episode of treatment (i.e., from the first to the last day of treatment). These studies of medical care utilization do not adequately capture the dynamic aspects of health care demand from the first day of sickness to the last day of sickness. Analysis of daily medical care consumption decisions allows for more accurate measurement of the effect of treatment on recovery as well as measurement of contemporaneous, non-productive effects of seeking care. The model described in this paper considers these absence and treatment behaviors jointly and provides useful information for policy reform.

This model addresses several issues that are missing in the absenteeism and medical care demand literatures and provides a framework for expanding our understanding of illness-related absence and treatment behavior. By estimating this dynamic episodic behavior over an entire year we can learn how specific annual sick leave characteristics (e.g., stock of leave and alternative reimbursement schemes) and insurance parameters (e.g., deductibles and maximum deductible amounts) influence the decisions to miss work and to seek treatment. One may also wish to model the effects of absence and treatment decisions on changes in health over time that may influence future illness contraction and recovery probabilities. Furthermore, the framework can be used to explore how learning about one's illness type might alter absence and treatment behavior during an episode of illness. These issues remain for future investigation.

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Appendix. Estimated likelihood function

Let $\bar{I}$ denote the set of individuals who are observed to have an acute illness episode. Individuals for which an illness episode is not observed belong to the set $\tilde{I}$ where $\tilde{I} \cap \bar{I} = \emptyset$ and $\tilde{I} \cup \bar{I} = I$, the set of all individuals in the estimation sample. The likelihood contribution of individuals never observed to be sick consists of the probability that an individual never contracted an acute illness throughout the entire year, $p(E = 0)$, plus the probabilities that e acute illness episodes occurred but none involved an absence or a doctor visit, $p(E = e \cup N = 0)$, where $p(i \in \tilde{I}) = p(E = 0) + \sum_{e=1}^{\bar{E}} p(E = e \cup N = 0)$.

The contribution to the likelihood function of individuals who are observed to have an acute illness episode, $\bar{I}$, consists of behavior prior to and during the observed illness episode. Let E^f represent the number of episodes in the f days prior to the first observed illness and N^f, the number of absences or visits during the episodes occurring within those f days. The probability of never having a recorded acute illness in f days is $p(E^f = e \cup N^f = 0)$. Once an illness episode is observed, the probability of observing one's particular behavior over that episode completes his contribution to the likelihood function. The probability of observing behavior b_i conditional on having an illness of type k is

$$p(b_i \mid k) = \left(\prod_{t=1}^{T_i}\left[\left(1-\pi^W(\mathbf{z}_t)\right)\prod_{j=1}^{J} p(d_{it}^j = 1 \mid \mathbf{z}_t)^{d_{it}^j}\right]\right) \times \pi^W(\mathbf{z}_{T_i+1})$$

where T_i denotes the last day of the acute illness episode for individual i.

The probability of a particular out-of-pocket responsibility, $\boldsymbol{\theta}$, for those who are uninsured ($i \in U$) is allowed to vary by health status. The expression ν_k represents the probability that the illness contracted is a type k illness out of K possible acute illness types and is a function of the time-invariant daily probabilities of contracting illnesses of specific types conditional on being well, $\pi^S(k)$. Taking into account the unobserved illness types and the unobserved out-of-pocket responsibility for those who are insured ($i \notin U$) but do not seek treatment, the likelihood function is

$$\begin{aligned}
\mathcal{L}(\boldsymbol{\Theta},\boldsymbol{\theta}) = \prod_{i\in\bar{I}}\Bigg\{&\Bigg[\theta_\ell\Bigg(\Bigg(\sum_{e=0}^{\bar{E}} p(E^{f_i}=e\cup N^{f_i}=0\mid\ell)\Bigg)\\
&\times \sum_{k=1}^{K}\nu_k\pi^S(k)p(b_i\mid \ell,k)\Bigg)\Bigg]^{1(i\notin U,\ell \text{ observed})}\\
&\times \Bigg[\sum_{\ell=1}^{3}\theta_\ell\Bigg(\Bigg(\sum_{e=0}^{\bar{E}} p(E^{f_i}=e\cup N^{f_i}=0\mid \ell)\Bigg)\\
&\times\sum_{k=1}^{K} \nu_k\pi^S(k)p(b_i\mid\ell,k)\Bigg)\Bigg]^{1(i\notin U,\ell\text{ unobserved})}\\
&\times\Bigg[\Bigg(\sum_{e=0}^{\bar{E}}\big(p(E^{f_i}=e\cup N^{f_i}=0\mid i\in U)\big)\\
&\times\sum_{k=1}^{K}\nu_k\pi^S(k)p(b_i\mid i\in U,k)\Bigg)\Bigg]^{1(i\in U)}\Bigg\}\\
&\times\prod_{i\in\tilde{I}}\Bigg[\sum_{\ell=1}^{3}\theta_\ell p(i\in\tilde{I}\mid\ell)\Bigg]^{1(i\notin U)}\cdot\Big[p(i\in\tilde{I}\mid i\in U)\Big]^{1(i\in U)}.
\end{aligned}$$

References

Adams, P., Benson, V., 1992. Current estimates from the national health interview survey, 1991. Vital and Health Statistics 10, 184.
Allen, S., 1981. An empirical model of work attendance. Review of Economics and Statistics 63, 77–87.
Andrews, D., 1988. Chi-square diagnostic tests for econometric models: Theory. Econometrica 56, 1419–1453.
Barmby, T., Treble, J., 1994. Discrete choice in a dynamic model with endogenous constraints: Absence Among Workers Under an Experience-Rated Sickpay Scheme. Working Paper, University of Wales.
Barmby, T., Ercolani, M., Treble, J., 2002. Sickness absence: An international comparison. The Economic Journal 112, F315–F331.
Barmby, T., Orme, C., Treble, J., 1991. Worker absenteeism: An analysis using microdata. The Economic Journal 101, 214–229.
Barmby, T., Orme, C., Treble, J., 1996. Worker absence histories: A panel data study. Labour Economics 2, 53–65.
Barmby, T., Sessions, J., Treble, J., 1994. Absenteeism, efficiency wages and shirking. Scandinavian Journal of Economics 96, 561–566.
Blau, D., Gilleskie, D., 2008. The role of retiree health insurance in the employment behavior of older males. International Economic Review 49, 475–514.
Broström, G., Johansson, P., Palme, M., 2004. Economic incentives and gender differences in work absence behavior. Swedish Economic Policy Review 11, 33–63.
Brown, S., 1994. Dynamic implications of absence behaviour. Applied Economics 26, 1163–1175.
Brown, S., Sessions, J., 1996. The economics of absence: Theory and evidence. Journal of Economic Surveys 10, 23–53.
CCH,. 2006. CCH Human Resources Management Ideas & Trends Newsletter, 2006 CCH Unscheduled Absence Survey.
Chan, T., Hamilton, B., 2006. Learning, private information, and the economic evaluation of randomized experiments. Journal of Political Economy 114, 997–1040.
Chaudhury, M., Ng, I., 1992. Absenteeism predictors: Least squares, rank regression, and model selection results. Canadian Journal of Economics 25, 615–635.
Crawford, G., Shum, M., 2005. Uncertainty and learning in pharmaceutical demand. Econometrica 73, 1135–1174.
Davis, M., Foster, E., 2005. A stochastic dynamic model of the mental health of children. International Economic Review 46, 837–866.
Fichman, M., 1989. Attendance makes the heart grow fonder: A hazard rate approach to modeling attendance. Journal of Applied Psychology 74, 325–335.
Gilleskie, D., 1998. A dynamic stochastic model of medical care use and work absence. Econometrica 66, 1–45.
Grossman, M., 1972. The Demand for Health: A Theoretical and Empirical Investigation. Columbia University Press, New York.
Harrison, D., Hulin, C., 1989. Investigations of absenteeism: Using event history models to study the absence-taking process. Journal of Applied Psychology 74, 300–316.
IBI., 2006. The business value of health: Linking CFOs to health and productivity, research by The Integrated Benefits Institute.
Johansson, P., Palme, M., 1996. Do economic incentives affect work absence? Empirical evidence using swedish micro data. Journal of Public Economics 59, 195–218.
Johansson, P., Palme, M., 2002. Assessing the effects of public policy on worker absenteeism. Journal of Human Resources 37, 381–409.
Johansson, P., Palme, M., 2005. Moral hazard and sickness insurance. Journal of Public Economics 89, 1879–1890.
Kahana, N., Weiss, A., 1992. Absenteeism: A comparison of incentives in alternative organizations. Journal of Comparative Economics 16, 573–595.
Khwaja, A., 2010. Estimating willingness to pay for medicare using a dynamic life-cycle model of demand for health insurance. Journal of Econometrics 156, 130–147.
Leigh, J., 1989. Specific illnesses, injuries, and job hazards associated with absenteeism. Journal of Occupational Medicine 31, 792–792.
Leigh, J., 1991. Employee and job attributes as predictors of absenteeism in a national sample of workers: The importance of health and dangerous working conditions. Social Science Medicine 33, 127–137.
Mira, P., 2007. Uncertain infant mortality, learning, and life-cycle fertility. International Economic Review 48, 809–846.
Paringer, L., 1983. Women and absenteeism: Health or economics? American Economic Review 73, 123–127.
US Department of Health and Human Services., 1980. The International Classification of Diseases (9th Revision, Clinical Modification). Washington: Government Printing Office.
Vistnes, J., 1997. Gender differences in days lost from work due to illness. Industrial and Labor Relations Review 50, 304–323.