Health and sick leave - policy makers' trade-offs

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Abstract

This paper is built on a simple idea that work is healthy for healthy workers, while it may delay recovery for sick workers. Its main novelty is that it sets out a theory designed to integrate this simple idea into a more standard labor supply model, where workers trade off absence and leisure against the economic loss involved. A calibrated version of this model is then used to discuss optimal sickness insurance policies. The results are: (i) there is a conflict between maximizing health and minimizing sick leave, (ii) optimal sick-leave benefits are neither zero nor 100 percent, (iii) a calibrated version of the model predicts optimal sick-leave benefits to be around 70 percent of earnings.

1 Introduction

The design of optimal social insurance policies often involves difficult trade-offs. This paper discusses one such trade-off, namely that between health and sick leave. The basic idea is that work is healthy for healthy workers, while it may delay recovery for sick workers. This implies that if absence is "too costly", workers may go to work even when they should have stayed at home. If absence is "too inexpensive", they may stay home even when they should have gone to work. The main novelty of this paper is that it sets

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out a theory designed to integrate this simple idea into a more standard labor supply model, where workers trade off absence and leisure against the economic loss involved. A calibrated version of this model is then used to discuss optimal sickness insurance policies, with particular emphasis on Norway and the United States.

The model presented allows for several policy variables to affect sick leave. These are sick-leave benefits, unemployment benefits and job-security. However, key in the model is the suggested health dynamics. These are an attempt to incorporate what I believe to be most physicans' advice to employees if they are ill: rest if you are sick, otherwise go to work. This is implemented in the model through a law of motion for health which is such that working when ill makes health worse, while working when not ill is good. The model is solved by finding an agent's decision rule which specifies for which levels of health he chooses work or sick leave, conditional on the policy variables. These policy variables constitute the *pressure* to which workers are subjected, moving the decision rule "up" and "down". Up means that the worker chooses sick leave for levels of health at which he would have worked if he were subjected to more pressure. Down means that he chooses to work for health levels at which he would have chosen sick leave if he were under less pressure.

By simulating this model one obtains predictions for health and sick leave. Some of these predictions are as expected. Low levels of pressure involve high sick leave. (Very) high levels of pressure imply poor health, as workers never really recover from their illness. As the amount of pressure is reduced, health improves, but in a non-linear fashion such that health improvements are large to begin with and then peter out. Interestingly, high levels of pressure may also lead to high levels of sick leave - because workers of poor health "bounce back and forth" between work and sick leave. Hence, for certain parameterizations of the model there is a U-shaped relationship between sick leave and work incentives. As we move from low to high pressure, sick-leave patterns change. Workers under high pressure have short but frequent absences. As the pressure decreases, the incidence rate for sick leave falls while the mean duration of sick-leave spells increases. As one approaches the lowest levels of pressure, both the incidence rate and duration increase until all workers are absent all the time.

A calibration exercise confirms these intuitions and may cast some light on the possible magnitudes. The model is calibrated using two sets of data: self-reported health data from Center for Disease Control in the US, and data for sick leave in 11 OECD countries. The calibration exercise is carried out by finding the parameters which best match predicted statistical moments from the model with real world analogues in the data. Finally, the calibrated model is used to investigate the predicted effects on health, sick leave and expected utility from changes in sick-leave benefits. More specifically, the effects of introducing more sick-leave benefits in the US and less sick-leave benefits in Norway are investigated.

The results of the model are as follows: Having no sick-leave benefits is not optimal because the increase in sick leave from making sick-leave benefits more generous are small compared to the gains in health. Nor is full wage replacement during sickness optimal. By reducing sick-leave benefits somewhat, sick leave falls substantially while health is kept almost unchanged. The predicted optimal amount of wage replacement during sickness is around 70 percent.

The rest of this paper is structured as follows. Section 2 discusses the modelling strategy, related literature and the use of health and health data in models. Section 3 presents a simple two-period version of the model which is useful to illustrate the decision rule and how it is affected by pressure. Section 4 presents a simulation exercise that investigates the aggregate predictions of the health dynamics suggested, for different levels of pressure and for three different parameterizations. Section 5 presents first an infinite horizon version of the model. It then presents the calibration exercise before the policy experiments are conducted and the results are discussed. Section 6 concludes.

2 Sick leave, health and labor market policies

This paper rests on the presumption that sick leave is an individual choice taken conditional on health and a set of policy variables. The analysis can be divided into two parts. First, an individual's decision making problem is considered and the modelled agent chooses between going to work or staying home on sick leave. A number of factors will affect his decision. First, and foremost, how sick is he really? Second, what are the consequences of his actions? If he stays home, what is he paid? How will it affect his career prospects or his job-security? If he looses his job, how is it to be unemployed? How will if affect his health if he chooses *not* to stay home? The ambition of this paper is to construct a framework for analysing these questions and to obtain answers - or at least some guidance - regarding what and optimal policy could be. Key in the analysis is the outcome of the individual decision making problem, the decision rule - saying for which levels of health the agent chooses work or sick leave, conditional on a set of labor market policy variables. This line of thought is closely related to a model developed by Barmby et.al (1994).

I term the *sum* of these labor market policies, moving the decision rule "up" and "down", *pressure.* Pressure is simply the cost of being absent. When deciding between work or sick leave, agents compare the outcome from staying home with the outcome from going to work and choose what maximizes their expected utility. The search for optimal policies are thus reduced to finding the optimal amount of pressure such that workers' decisions are socially optimal. Many empirical papers in Economics have studied the consequences of generous welfare schemes on sick leave. We know from these studies that such welfare schemes affect sick leave substantially (see e.g. Henrekson and Persson, 2004; Johansson and Palme, 2005). We also know that job-security is important for sick leave (Ichino and Riphan, 2005). The more theoretical approach in this paper makes it possible to take a somewhat wider view and the effects of pressure on both sick leave and health are studied. The inclusion of health is important for many reasons. First, health has an (obvious) impact on the need for sick leave (see Allen, 1981; Paringer, 1983; Leigh, 1991; French and Zarkin, 1999). Second, health is not just important as an explanatory variable for sick leave, it is also an outcome; whether workers choose to restitute from illness or not has an impact on their health. To my knowledge, no former studies combine such health dynamics with health modelled as a continuum. "A weakness of the economic literature on absenteeism, and in sharp contrast to the medical statistics literature has been the tendency of theoretical models to ignore the state of the individual's health" (Brown and Sessions, 1996, p. 42). When health is modelled, it is often modelled discrete, i.e. "good" og "bad", as in Kahana and Weiss (1992). "This approach is clearly unrealistic since an entire spectrum of states of health exists which leads to a complex interaction between the absence decision and health status. (Brown and Sessions, 1996, p.45). When health is made endogenous we can think of situations with too little or too much pressure. Too little pressure leads to high absence rates. Too much pressure can lead to poor health as workers are not allowed to recover from illness.

To illustrate how the amount of pressure can exceed what is socially optimal let me give an example: Consider a firm employing a freshman; young, newly educated with little or no work experience. The employer knows little about this worker's health-status. The beginning of a working career can be very important; many employers practice a "trial-period" or use temporary contracts as a screening device for new workers. Not being offered a pro-longed work contract after the trial-period is doubly bad for the worker; in addition to loosing the job, it also serves as a warning signal for future employers. Consider the situation where this newly employed worker feels somewhat sick and must decide whether or not to go to work. For the employer, the cost of loosing one employee a short period of time is small. For the employee, the cost may be very high - if his employer starts suspecting him of beeing of poor health.

When employers hire workers they have limited knowledge of these workers' health, abilities and skills. Even if workers' true attributes are unobserveable, behavior is not. Over time, employers get to know their employees better. It is convenient to think of this learning process as employers receiving a *signal with noise* of their employees' true attributes. If an employee calls in sick once, the employer gets only some information about this workers long-term health status. However, over time, employers become better and better informed, as differences between workers are increasingly unlikely to be the result of coincidence. In the model to be presented, long-term costs of sick leave are collapsed into one single mechanism: reduced job-security. Sick leave is assumed to increase the probability of unemployement. "A major criticism of almost all theoretical models of sick leave to date is their ignorance of such dynamic considerations. As Carlin (1989) has observed, the detection of shirking does not always lead to immediate dismissal. Hence, the interaction between workers and employers should be modelled as in a repeated game - i.e. the time horizon should be extended" (Brown and Sessions, 1996, p.45).

It is important to specify what is meant by the term *health.* There is no such thing as a consensus on a definition of health. As commented by Mordacci and Sobel (1998): "Health is one of those every day slippery-as-mercury-words, the meaning of which seems obvious and self-evident, that we seldom take a few moments to define the term consciously for ourselves". There is however a large literature and several schools of thought. Boorse (1977) represents the biomedical school of thought and defines health as: "...normal, functional ability. The readiness (...) to perform all its normal functions on typical occasions with at least typical efficiency." This is the kind of definition that best describes how health is used in this paper. Health is thus defined "negatively" as *absence of illness*, or in other words: if there is nothing wrong with you, you are in good health. However, the reader should be aware that there are other schools. Health can also be defined "positively" as presence of happiness, well-being, energy, etc. WHO defines health as "Health is a state of complete physical, mental, and social well-being, and not merely the absence of disease or infirmity." (World Health Organization, 1948).

In this paper health is going to be subjectively evaluated by the decision maker. An agent's health status is a measure of his physical and mental ability, and not the result of a physician's evaluation. This agent will have an opinion on whether going to work - not restitute - will make him worse or not. He will also have an opinion on the expected time needed for restitution, conditional on whether he chooses restitution or work. To capture all sorts of health in one variable is obviously a huge simplification. However, to make the model tractable, simplifications are needed.

The measures of health used in this studiy are self-reported. Bound (1991) investigates the consequences of using self-reported vs. objective measures of health in retirement models. Self-reported measures can be problematic for a number of reasons. Most important is probably that since "health may represent one of the few "legitimate" reasons (...) to be out of work, men out of the labor force may mention health limitations to rationalize their behavior" (Bound 1991, p.106). "Myers (1982,1983) has gone so far as to argue that there is no useful information in self-evaluated health" (Bound, 1991, p.106). The alternative to self-reported health would be some objective health measure such as expected life length, physical examination of verifiable illnesses etc. However, even if such data should be available they may also be problematic as the majority of absence spells stems from diagnoses hard or impossible to verify such as lower back pain or mental illness. Bound (1989) shows, and argues, that self-reported and objective measures both suffer from biases, but with opposite signs. When self-reported measures of health are used for labor supply studies, the importance of health will easily be exaggerated. When crude objective measures are used, such as expected life length, the opposite problem will occur. Bound (1989) argues that self-reported and objective measures of health constructs an upper and lower bound of the impact of health on labor supply decisions. The main reason for using self-reported health data in this paper is however purely pragmatic. Sick leave is a short-run phenomenon, lasting for days, weeks or months and data for objective health measures with such fine partitioning of time is - to my knowledge - not publicly available. To reduce the potential bias from using such data I will primarily use data for employed people ("active" vs. "inactive").

3 A simple two-period model for health, sick leave and pressure

Consider a worker maximizing utility over two periods with preferences over consumption c_t, leisure $l_t \in \{0,1\}$, and health h_t. His preferences are represented by a utility function separable across time and in the three arguments. Utility from health is assumed to be linear, with marginal utility θ. The applied utility function is given by (1), where $\delta \in (0,1)$ is the discount factor.

$$u(c,l,h) = \sum_{t=1}^{2} \delta^{t-1} \left[u(c_t) + \eta l_t + \theta h_t \right] \tag{1}$$

In this model, health is an endogenous variable dependent on past health and sick leave. Hence, my health tomorrow is a function of my health today and of whether I today worked or was absent. To keep the model as simple as possible health is now considered to evolve deterministicly. In the subsequent sections health will be a stochastic variable. However, for building intuition this simple set-up is useful. Health is also assumed to be bounded by an upper and a lower limit, denoted h_H and h_L respectively. Within these bounds health evolves across time in accordance with a law of motion given by (2)[1].

$$h_{t+1} = h_t + \begin{cases} \alpha \left(h_t - h^W \right) : \text{if working} \\ \alpha \left(h^P - h_t \right) : \text{if at home} \end{cases} \tag{2}$$

[1] To simplify the parameter α governs both health evolvement when working and staying at home. This make the problem symmetric and the results simpler. No results rest on this assumption.

Working when health is below h^W is unhealtful. This capture situations in which restitution is needed to recover. h^P is the long-term health level for the absentees. When absent, h approaches h^P regardless. When $h < h^P$ this process is restitution. Note that h^P may or may not be lower than h_H. If $h^P < h_H$ the law of motion implies that inactivity is unhealthful for healthy people.

Both h^W and h^P should be thought of as subjective and observeable by the agent only. To make the problem meaningful assume also that $h^P > h^W$ such that restitution is possible. The state space of health can then be divided into three intervals, illustrated in Figure 1 below. (i) When health is betwen h_L and h^W it will improve if the agent is absent and worsen if he works. (ii) For levels of health between h^W and h^P health will improve anyhow. From the symmetry of (2) health will improve faster if he stays home when h is closer to h^W and works if h is closer to h^P. The *decision rule* is a threshold for health that is such that the worker chooses absence if health is below and work if health is above. We denote the decision rule that maximizes health $h^* = \frac{h^P + h^W}{2}$. (iii) When health is between h^P and h_H it will improve when he works and worsen if he stays home.

Let me give a few examples. Think of an agent in poor health such that $h < h^W$. He can choose to stay home and restitute or he can go to work, but must then expect health to worsen next period. Clearly, he faces a trade-off between health and economics. Next, consider a situation where $h^W < h < h^P$. The agent can expect health to improve regardless of whether he chooses to work or stay home. He will then trade off expected time for restitution against economic incentives and leisure. Finally, consider a situation where $h > h^P$. The agent is perfectly capable of working, and from a health perspective, he should be working. He will also trade off health against economic incentives and leisure.

Standing in period 1, the worker's problem is whether to work or stay home this period. If he chooses to work he receives earnings W. If he stays home he receives benefits $B = bW$. When making up his mind, he must also take the future consequences of his actions into consideration. Health in period 2 will be determined by his decision in period 1. Below the problem is analysed in two stylized cases: one with full job-security and one with no job-security.

Full job-security Full job-security implies that whether the agent worked or was absent in period 1 has no impact on employment in period 2. We want to solve the model by

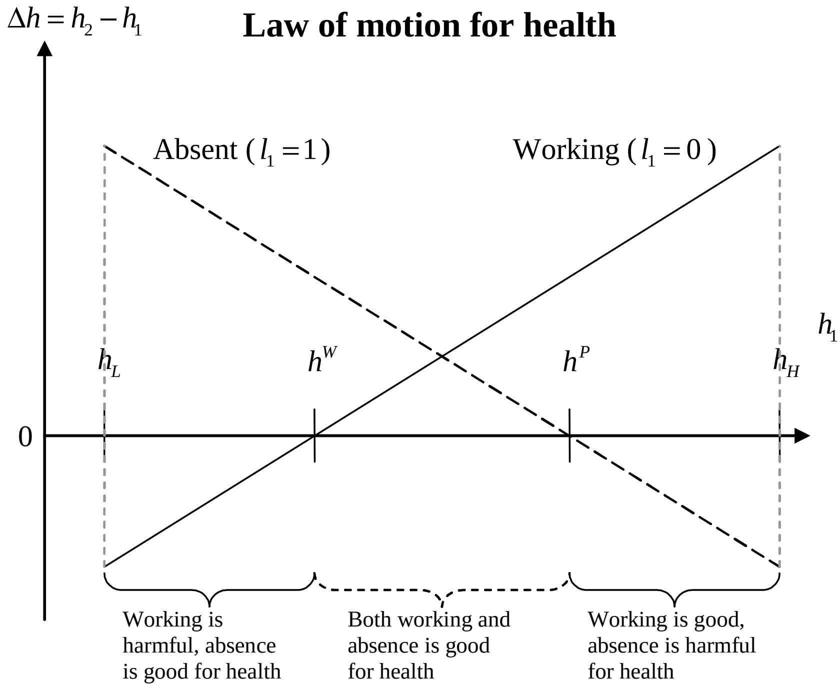

Figure 1: **Law of motion for health.** The figure illustrates the law of motion for health and the assumptions made regarding the health effects from working and leisure. The state space for health can be divided into three regions. For low levels of health ($h < h^W$), working is harmful while absence is good. For intermediate levels of health ($h^W < h < h^P$), both working and absence is good. For high levels of health ($h > h^P$), working is good while absence is harmful.

finding the levels for health at which the worker chooses to work or be absent. To solve the worker's problem we start in period 2. Utility in period 2 is given by:

$$v_2 + \theta h_2 = \max \left[u \left(W \right), u \left(B \right) + \eta \right] + \theta h_2$$

The decision in period 2 is independent of health since there is no third period. If the worker chooses to work in period 1 his utility is given by (3). If he chooses to stay home his utility is given by (4).

$$u_1^W = u(W) + \theta h_1 + \delta \left(v_2 + \theta \left[h_1 + \alpha \left(h_1 - h^W \right) \right] \right) \tag{3}$$

$$u_1^A = u(B) + \eta + \theta h_1 + \delta \left(v_2 + \theta \left[h_1 + \alpha \left(h^P - h_1 \right) \right] \right) \tag{4}$$

Hence, the worker's problem in period 1 is simply to choose the largest of u_1^W and u_1^A. Since these expressions are linear in health we know that there exists a level of health such that $u_1^W = u_1^A$, and that when health is above (below) this level the worker will choose to work (be absent). This level of health, making the worker indifferent between work and sick leave, is the decision rule $\hat{h}$ and is simply found by solving the equation $u_1^W = u_1^A$ for h. In the case of full job-security, the decision rule is given by (5).

$$\hat{h}^F = \frac{h^W + h^P}{2} - \frac{u(W) - u(B) - \eta}{2\delta\theta\alpha} \tag{5}$$

Consider first the case when $u(W) - u(B) - \eta = 0$. The optimal decision rule is simply h^*, which maximizes health. When the agent is indifferent between the wage from working and the benefit together with the leisure from staying home he will choose to stay home when this is best for his health and work otherwise.

In some countries workers have full wage compensation ($B = W$) when ill. In this setup the worker will choose to stay home for health levels where his health would benefit from working, because of the additional utility from leisure. When $B = 0$ the worker may choose to work for health levels at which working is harmful.

No job-security No job-security implies that a worker who stays home in the first period is unemployed with certainty in the second period. When unemployed he receives a benefit B, equal to the amount he receives when ill. In most countries unemployment benefits are different from sickness benefits, but at this stage this is of little importance.

Again we start in period 2 to solve the worker's problem. Utility in period 2 is now dependent on the decision in period 1, since the agent is unemployed in period 2 if he was absent in period 1. If he worked in the first period, his problem in period 2 is the same as in the case of full job-security above. If he stayed home, utility in period 2 is given by $u(B) + \eta + \theta h_2$. Sick leave in period 1 now results in a loss of opportunities in period 2. Whether this loss of opportunities is of any value depends on whether $u(W) > u(B) + \eta$ or not. The opportunity to work is valued by $v_2^O = v_2 - u(B) - \eta$. The model can then be solved in the exact same manner as above and the resulting decision rule is given by (6).

$$\hat{h}^N = \frac{h^w + h^P}{2} - \frac{u(W) - u(B) - \eta}{2\theta\delta\alpha} - \frac{v_2^O}{2\theta\alpha} \tag{6}$$

As in the case with full job-security, the worker chooses what is optimal for his health if $u(W) - u(B) - \eta = 0$. Also if $u(W) < u(B) - \eta$ the cases with full job-security and no job-security are identical. The reason is simple: if the agent never prefer to work in period 2 anyhow, there is no loss in utility from losing the opportunity to work. If $u(W) > u(B) - \eta$ the two cases differ. In the case of no job-security, the worker will go to work for lower levels of health than in the case of full job-security in order to remain employed next period.

Short term and long term consequences To build some intuition we can investigate the impact of letting $\delta \to \infty$. This will loosely correspond to an infinite horizon problem with a (very) patient agent. Period 2 should then be interpreted as the rest of his life. In the case of full job-security $\lim_{\delta\to\infty} \hat{h}^F = h^*$. Hence, short term economic incentives have no impact on the decision rule as the economic cost of staying home one period last only that period while the consequences for health last for all future periods. The worker chooses consequently to follow the decision rule that maximizes health h^*. In the case of no job-security $\lim_{\delta\to\infty} \hat{h}^N = h^* - \frac{v_2^O}{2\theta\alpha}$. Now economic incentives has an impact on the decision rule. The reason is that the economic cost of staying home last forever, since he looses his job.

4 Pressure, sick leave and health: a simulation exercise

As seen above, the decision rule can be thought of as a function of the amount of pressure to which workers are subjected. High pressure forces employees to work, also when doing so is unhealthful. Low pressure makes employees stay at home, also when they are perfectly able to work. In this section, the effect of pressure on sick leave and health is studied using a reduced form approach. Pressure is represented *directly* by the decision rule. The exercise is *reduced form* in the sense that we study the predicted sick-leave rates and health levels *given* various decision rules. The complete structural exercise would be to first use the theory model to obtain a decision rule conditional on policy variables, and then simulate the model to obtain direct predictions from policy changes on sick leave and health. This is the approach taken in Section 5. As the model's predictions inevitably will depend on the chosen parameters I believe it is illuminating first to learn more about the "mechanical" implications of different decision rules and parameterizations.

We now leave the two-period setting and consider a dynamic model with infinitely many periods. The starting point of this exercise is a stochastic version of the law of motion for health, given by (7).

$$h_{t+1} = h_t - \varepsilon_{t+1} + \begin{cases} \alpha \left(h_t - h^W\right) : \text{if working} \\ \alpha \left(h^P - h_t\right) : \text{if at home} \end{cases} \tag{7}$$

ε_{t+1} is a random health shock, drawn from some distribution of health shocks and realized in $t+1$. Given a decision rule, a specified distribution of ε, and the parameters h_L, h_H, h^W, h^P, and α, the model can easily be simulated by drawing health shocks and let simulated workers "choose" to work or be absent in accordance with the decision rule. It turns out that the predictions from such a simulation is independent of the initial vector of health, a necessary condition for such an exercise to be meaningful.

Parameterization The lower and upper bounds for health are set to 1 and 100, and the simulation exercise is carried out for decision rules equal to all integers between 1 and 100. The remaining three health parameters and the so far unspecified health shock, allow for a large number of possible combinations, far too many to be shown here. I will thus restrict the exercise to some specific cases I find useful to build intuition regarding the implications of the model.

The time unit weeks. Every week, each worker draws a health shock. It seems intuitive that the distribution of health shocks is skewed such that the health shock most of the time is close to zero and negligable. Every now and then, the worker draws a substantial health shock - he becomes sick. In this simulation exercise the health shocks are drawn from a log normal distribution. After these shocks are drawn, the expected value of this shock, $\bar{\varepsilon}$, is substracted such that the expected value of the health shock is equal to zero. The log normal distribution has two parameters (μ, σ). These are set quite roughly to provide the shock with reasonable properties. The chosen values are $(\mu, \sigma) = (0.1, 1.6)$ which implies the following probabilities: $P(\varepsilon > 5) = 0.095$, $P(\varepsilon > 50) = 0.008$, and $P(\varepsilon > 95) = 0.003$. During one year, this implies that nearly everyone are hit at least once by a health shock of more than 5. 32 percent are hit at least once by a health shock of more than 50, and 12 percent are hit by a health shock of more than 95.

It is hard to determine h^P and h^W without comparing outcomes from the model with data. Since this exercise is mainly intended to inspect the qualitative implications of the model I will test three different cases. The first is that $h^P = h_H$ and $h^W = \frac{1}{2}h_H$ such that the possible negative effect of inactivity is assumed away. The negative effect of working when sick is however present. The second case is that $h^P = \frac{2}{3}h_H$ and $h^W = \frac{1}{3}h_H$. In this case, both health mechanisms are at work. In the third case, $h^P = h_H$ and $h^W = h_L$. Hence, in this case the expected change in health $E[h_{t+1} - h_t]$ is positive regardless of h_t and whether the agent work or are on sick leave (apart from when $h = h^H$). Still, how fast health improves depends on h and the work/sick-leave decision. These three cases will, qualitatively, cover most relevant cases.

The parameter α regulates the speed of health transitions. When on sick leave, α is the fraction of the gap $h^P - h_t$ the worker catches up during one week. It turns out that α is important for the level of sick leave and health, but not so important for understanding the qualitative predictions of changes in the decision rule. α is set such that the fastest possible transition from h_L to h_H is 20 weeks when we disregard the health shocks. α is consequently different in the three cases mentioned above: $(\alpha_1, \alpha_2, \alpha_3) = (0.110, 0.145, 0.073)$.

The model is simulated for 10 000 agents over 500 periods. The last 100 periods are

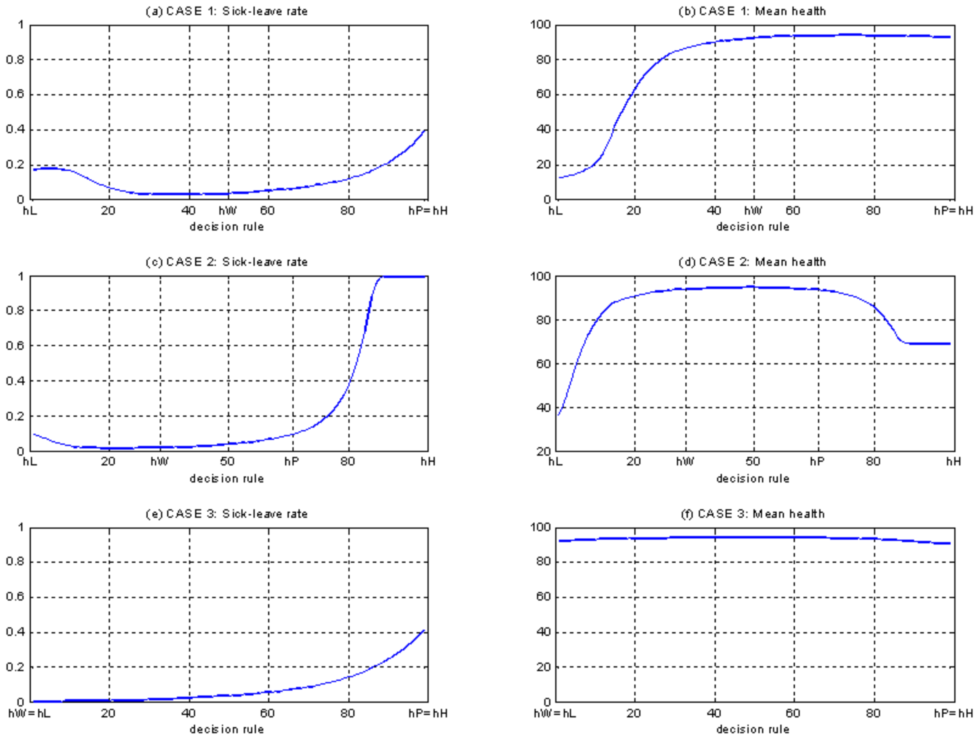

Figure 2: **Simulated sick leave and health.** Panels (a, c, e) show how sick leave changes when the decision rule changes from h_L to h_H. Panels (b, d, f) show the corresponding changes in mean health. Panels (a, b) show predictions from Case 1 where $h^P = h_H$ and $h^W = \frac{1}{2}h_H$. Panels (c, d) show predictions from Case 2 where $h^P = \frac{2}{3}h_H$ and $h^W = \frac{1}{3}h_H$. Panels (e, f) show predictions from Case 3 where $h^P = h_H$ and $h^W = h_L$.

used for calculating the statistics displayed in the Figures 2, 3 and 4.

Figure 2 displays the sick-leave rate and mean health in each of the three cases described above. Panel (a) plots the sick-leave rate as a function of the decision rule for the case where $h^W = \frac{1}{2}h^H$ and $h^P = h_H$. We see that this relationship is U-shaped. In the case where the agent chooses to work even for low levels of health sick leave is fairly high. In an intermediate range, when the agent's decision rule is in the neighborhood of h^W, sick leave is fairly low. As the decision rule exceeds h^* sick leave increases sharply. Panel (b) draws the corresponding means of health. In the cases where workers's decision rule is below $h < \frac{1}{2}h^W$ health is poor. The reason is that when these workers catch an illness they are first absent for a week or two before they return to work. However, since $h < \frac{1}{2}h^W$, working is unhealthful and in term they must return to sick leave. Consequently, these workers may "bounce back and forth" between work and sick leave and never recover. As the decision rule increases, workers recover more before they return to work.This leads to a drop in sick leave and an increase in health. After the decision rule exceeds h^W, health is fairly stable and reaches its maximum when the decision rule is equal to h^*.

Case 2, where $h^W = \frac{1}{3}h_H$ and $h^P = \frac{2}{3}h_H$, is qualitatively similar to Case 1 when we consider simulated sick leave, displayed in Panel (c) of Figure 2. The most important difference is that since $h^P < h_H$ workers, whose health would have benefited from working, now stay home when the decision rule exceeds h^P. This leads to a decline in health. When the decision rule is sufficiently close to h_H, no one works and average health deteriorates down to h^P. This parameterization thus involves an *inactivity trap*.

Case 3, in which $h^W = h_L$ and $h^P = h_H$, gives a different picture than the two preceding, and is displayed in Panels (e) and (f). Remember that now the parameters are set such that restitution never is necessary. It merely helps to speed up recovery when health is bad. Sick leave is now increasing monotonically in the decision rule at an increasing speed. Hence, the non-linearity at the top is kept while the U-shape is no longer present. Health is maximized at h^*. Compared to Case 1 and 2, the changes in health from changing the decision rule are small.

Figure 3 displays incidence rates and mean durations of sick-leave in each of the three cases. The incidence rate is calculated as the number of new spells in a given week, dividied by the number of workers *at risk* of starting a new spell.

Duration is strictly increasing in the decision rule, in all three cases. This is fairly intuitive as workers are allowed to recover for a longer period after any health shock. In Cases 1 and 2, the incidence rate is U-shaped in the decision rule, reflecting the discussion from above regarding why sick leave is fairly high also when the decision rule is (very) low. In these cases workers go back and forth between work and sick leave and never recover from their illness. The incidence rate is relatively low for intermediate levels of the decision rule until it starts to increase when the decision rule approaches h_H. In Case 2 the incidence rate is not defined for the highest levels of the decision rule as all agents are on sick leave and no one is at risk for starting a new spell. Mean duration is in this case censored at 52, but these workers never work. Again Case 3 is different as also the incidence rate is increasing in the decision rule.

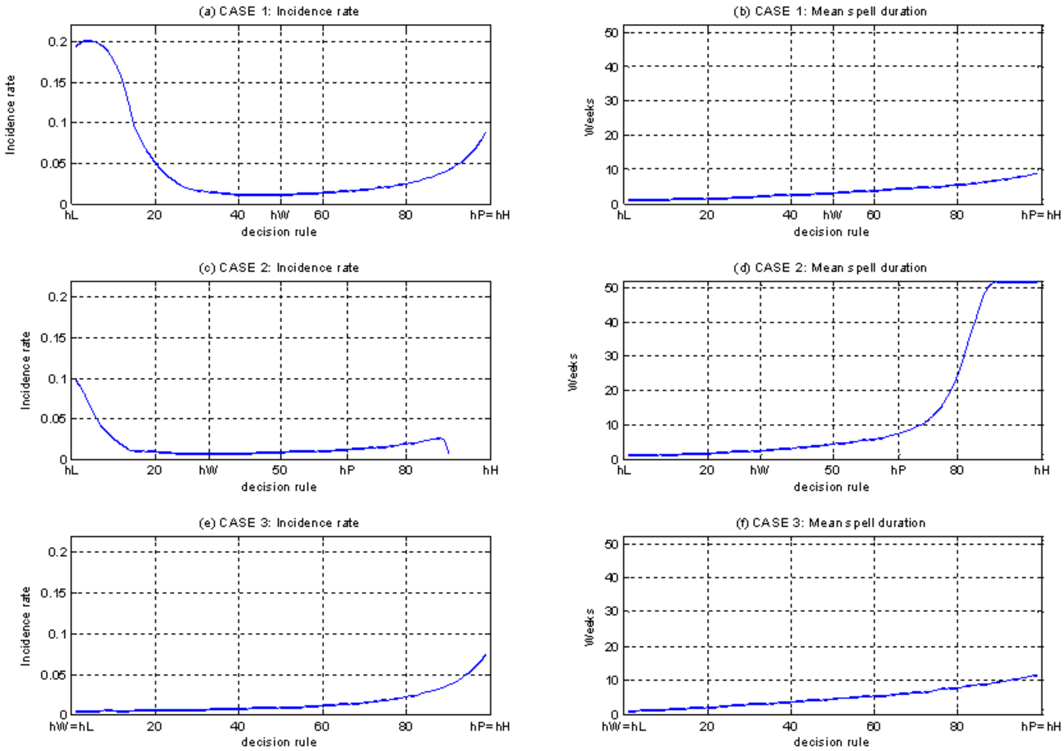

Figure 3: **Simulated sick leave incidence rates and spell durations.** Panels (a, c, e) show how the incidence rate to sick leave changes when the decision rule changes from h_L to h_H. Panels (b, d, f) show the corresponding changes in mean spell duration. Panels (a, b) show predictions from Case 1 where $h^P = h_H$ and $h^W = \frac{1}{2}h_H$. Panels (c, d) show predictions from Case 2 where $h^P = \frac{2}{3}h_H$ and $h^W = \frac{1}{3}h_H$. Panels (e, f) show predictions from Case 3 where $h^P = h_H$ and $h^W = h_L$.

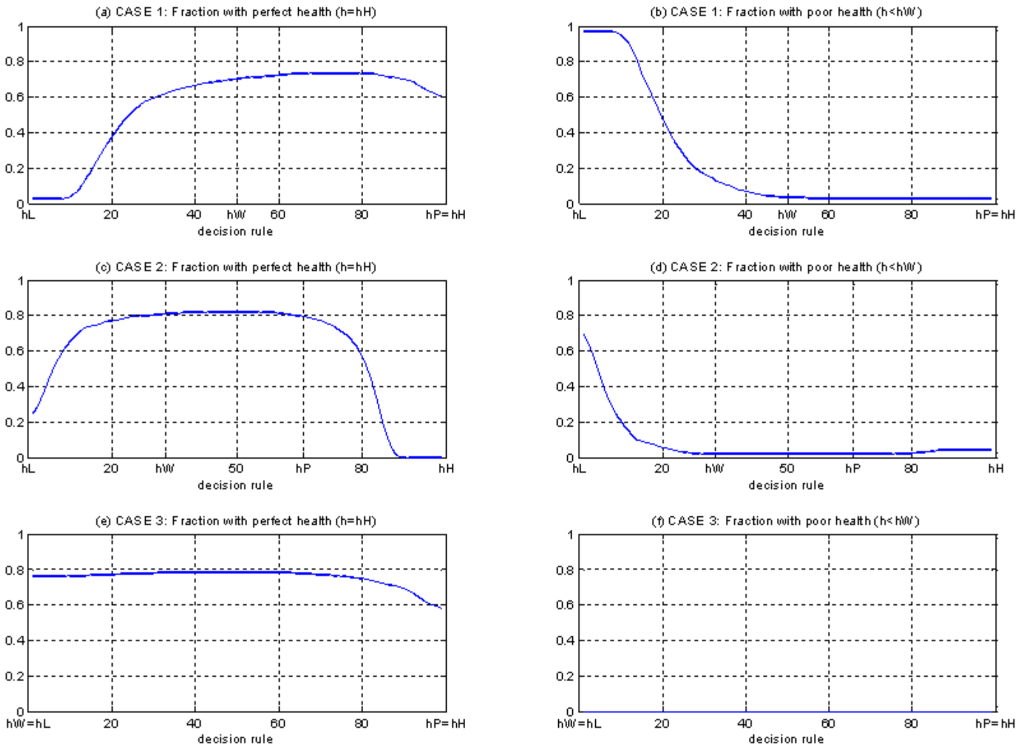

Figure 4: **Fractions with perfect and poor simulated health.** Panels (a, c, e) show changes in the fraction of workers with "perfect health", defined as $h = h_H$, when when the decision rule changes from h_L to h_H. Panels (b, d, f) show changes in the fraction of agents with "poor health", defined as $h < h^W$, as the decision rule changes from h_L to h_H. Panels (a, b) show predictions from Case 1 where $h^P = h_H$ and $h^W = h_H/2$. Panels (c, d) show predictions from Case 2 where $h^P = \frac{2}{3}h_H$ and $h^W = \frac{1}{3}h_H$. Panels (e, f) show predictions from Case 3 where $h^P = h_H$ and $h^W = h_L$.

Figure 4 provides some information concerning the distribution of health in the three cases. The left panels (a, c, e) show the fraction of workers with perfect health, i.e. $h = h_H$. The right panels (b, d, f) displays the fraction of workers in *poor health*, defined as the fraction of workers with $h < h^W$. By assumption, these workers have such poor health that working is unhealthful. In Case 3 no worker has poor health by definition, since $h^W = h_L$.

Three elements are worth mentioning from Figure 4. First, part from when the decision rule is well below h^W, most workers have perfect health. Second, when the decision rule is below h^W a signficant fraction of the population has poor health. When the decision rule is above h^W this fraction is reduced to a minimum. The reason is that when the decision rule exceeds h^W workers can restitute and recover until working no longer unhealthful. Third, the fraction of workers in perfect health is decreasing when the decision rule approaches h_H. The reason is that the law of motion is such that recovery is faster when working than absent when health exceeds h^*.

5 Application of the model

The non-linear relationships between pressure, sick leave and health motivate an exercise where we ask whether there are potential gains in terms of improved health or reduced sick leave from changes in sick-leave policies for countries on the "edges" of the policy space. More specifically, I will try to investigate the policy implications from this model applied to Norway and the US, with full and zero sickness benefits respectively.[2] In order to so the model must extended to a multi period setting that can be used to find specific decision rules as functions of policy. Such a model must be solved numerically and all parameters must thus be given specific values. Many of the parameters have no observed analogues in the real world. The parameters are set by comparing the model's predictions, which are dependent on the parameters, with corresponding moments from data. This section is first of all an illustration of how the model can be applied to data and real world problems. Several technicalities are left out allthough some are discussed in the

[2]In Norway, all workers are entitled to full wage replacement during sickness for earnings up to 6G (roughly 75 000 USD in 2009). In the US there are variation between states and employers but many employees, in particular low-wage workers do not have paid sick days (Lovell, 2007; Scruggs, 2004).

Appendix. It is important to stress that this exercise is intended to "fit the model" to the data, and is not an attempt to estimate the general structural parameters in the model. I refer to the fitting of this model as *calibration*.

The structure of this section is as follows: First, an infinite horizon version of the simple two-period model from Section 3 is presented. Then this model is calibrated to data. Finally, the calibrated model is used to apply two policy experiments: (1) reduced sick-leave benefits in Norway, and (2) increased sick-leave benefits in the US.

5.1 A dynamic model for health, sick leave and pressure

The two-period model from above for individual decision making can easily be extended to the infinite horizon. The choice of infinite horizon seems natural since the solution of such a model is independent of "age" or, more precisely, the number of periods left on the labor market. How behavior may change as workers approach the retirement age is an interesting question to investigate, but it is outside the scope of this paper. In the case where retirement is (sufficiently) far into the future, the infinite and finite horizon models are equivalent. Hence, this model should be thought of as a model of a worker with sufficient time left employed not to spend time thinking of his retirement. As in the previous section, each period corresponds to one week.

A serious limitation of this model is that there are no savings, implying that consumption and income is the same. One way to think of this is that the model is intended to explain behavior of relatively poor workers without subtantial savings.

Preferences and earnings As stated already, workers have preferences over consumption leisure and health and choose work or sick leave to maximize their expected utility.

$$\max_{\{l_t \in [0,1]\}_{t=0}^{\infty}} E \sum_{t=0}^{\infty} \beta^t u\left(c_t, l_t, h_t\right)$$

The utility function $u\left(c_t, l_t, h_t\right)$ is partly separable as it allows the utility of leisure to be dependent of health. Specifically, the disutility from work is allowed to be higher when health is poor. The utility function in (8) is a combination of the CRRA and CES classes of utility functions.

$$u(c_t, l_t, h_t) = \frac{(c_t + 1)^{1-\theta}}{1-\theta} + \varphi \frac{\left[\left(\xi l_t + h_t^{\phi} \right)^{\frac{1}{\phi}} \right]^{1-\theta}}{1-\theta} \tag{8}$$

Income is dependent on work and absence, as shown in (9). If he chooses to work he receives earnings W. If he is absent he receives a fraction b of his earnings dependent on the replacement rate for sickness. If he becomes unemployed, he receives a fraction b_t^U of earnings as unemployment insurance benefits.

$$c_t = y_t = \begin{cases} W \text{ if working} \\ bW \text{ if absent} \\ b^U W \text{ if unemployed} \end{cases} \tag{9}$$

Health dynamics The law of motion for health in (10) is slightly more flexible than the one used in Section 4 as the parameter α may differ between the working state and sick leave state.

$$h_{t+1} = h_t - \varepsilon_{t+1} + \begin{cases} \alpha_W \left(h_t - h^W \right) : \text{if working} \\ \alpha_H \left(h^P - h_t \right) : \text{if at home} \end{cases} \tag{10}$$

Note that the decision rule that maxmizes health now is given by $h^* = \frac{\alpha_W h^W + \alpha_H h^P}{\alpha_W + \alpha_H}$.

Law of motion for job-security and the unemployed state When the worker is absent, this affects his job-security negatively. Job-security π_t is the probability of still being employed next period. If the worker is absent π decreases, if he works π increases. Job-security is modelled simplistic and reduced form and follows the law of motion in (11).

$$\pi_{t+1} = \begin{cases} \pi_t + \gamma \left(\pi_H - \pi_t \right) \text{ if working} \\ \pi_t - \gamma \left(\pi_H - \pi_t \right) \text{ if absent} \end{cases} \tag{11}$$

π_H is the maximum job-security, close to one, and γ is a parameter that will be made a function of the degree of employment protection legislation.

If the worker becomes unemployed he makes no decisions. Every period he receives an unemployment benefit and there is a probability p that he receives a new job, similar to the one he had, and which he accepts. His health evolves as if he was on sick leave. The utility for an unemployed agent is given by (12). Time subscripts are removed and future values are simply denoted by marks. Since the problem is stationary nothing depends on

t as such, just the ordering of the periods.

$$V_U(h) = u(c,l,h) + \beta E\{(1-p) V_U(h') + pV(h',\pi')\} \tag{12}$$

The utility maximization problem The agent solves (13) subject to (8), 9, (10), (11) and (12).

$$V(h,\pi) = \max_{l\in\{0,1\}} u(c,l,h) + \beta E\{\pi V(h',\pi') + (1-\pi) V_U(h')\} \tag{13}$$

The model is solved numerically by value function iteration. In order to do so, the state space (h,π) is discretized. The primary focus of this paper is on decision rules as functions of health and I will thus restrict the reported results to a particular level of job-security. The decision rule can then be written $d(h|\pi^*) = d(h)$. There are also technical reasons for this (see appendix).

Different from the two-period model in Section 3, the decision rule is no longer necessarily such that the agent chooses to work (be absent) if health is above (below) a certain level. Dependent on the parameters, there may be several such thresholds where the agent changes from work to absence and back. Still, in the calibrated model below it turns out that the decision rule is of the simple form as in Section 3.

5.2 Calibration

5.2.1 Policy parameters

The decision making problem of the agent is conditional on a set of policy variables. These are exogenous to the problem and specific to each country i. There are four such parameters: (i) sick-leave benefits b_i, defined as the fraction of earnings received by the agent when he is on sick leave, (ii) unemployment benefits b_i^U, defined as the fraction of earnings received by the agent if he becomes unemployed, (iii) the probability of becoming employed when unemployed p_i, which is the inverse of mean unemployment duration[3], (iv), employment protection legislation EPL_i, used to determine γ_i and based on OECD's EPL index. These data originate from various sources and are presented in Table A1 in

[3] This is clearly a simplification but it reflects the way unemployment is modelled. Unemployed agents are (in expected terms) waiting in line for new jobs and there is nothing they can do to influence the job-finding process.

the appendix. For the presentation of the procedure for calibration it is useful to collect the policy variables in a vector $P_i = \{b_i, b_i^U, p_i, EPL_i\}$.

5.2.2 Structural parameters

There are no observed real world analogues to the remaining structural parameters in his model. To determined these parameters I apply an exercise in the spirit of *classical mimimum distance estimation* (Wooldridge 2002, p.442-446). In short, the purpose is to find the parameter values that makes the model's predictions as similar to data as possible.

It is convenient to collect the remaining parameters in two structures. First, if we restrict focus to distributions for ε with only two parameters (μ, σ^2), there are in total six health parameters which need to be determined: $H = \{h^P, h^W, \alpha_W, \alpha_H, \mu, \sigma^2\}$. The second group of parameters are related to preferences and job-security. Since the link between EPL and job-security is not immediate, I construct a linear function: $\gamma_i = \kappa_0 + \kappa_1 [C - EPL_i]$ where C is a fixed constant. The structure $\Theta = \{\theta, \varphi, \phi, \xi, \beta, \kappa_0, \kappa_1\}$ has consequently 7 parameters, all to be determined.

The parameters in H and Θ are considered *structural* in the sense that they are independent of policy and they are assumed to be similar across countries (and time). Two different data sources are used to construct statistical moments from data that can be compared with the model's predictions. First, data for self-reported health from the US are used to construct 6 moments for calibrating H. Second, absence data for 11 OECD countries (see Table A1) are used to construct 11 moments to calibrate the remaining 7 parameters in Θ. Notice that in such a sequential procedure, calibration of H will inevitably be made conditional on Θ and vice versa. An iterative procedure is thus employed. Let iterations be denoted with superscripts while country-specific variables are denoted with subscripts. The aim is to find H^{j+1} condition on Θ^j, and Θ^{j+1} conditional on H^{j+1}, repeatedly (as j increases) until $H^{k+1} = H^k$ and $\Theta^{k+1} = \Theta^k$.

To determine the two structures of parameters, H and Θ, the following iterative three-step procedure is employed.

1. Guess a set of initial parameters H^j and Θ^j, where $j = 0$.

2. Compute the decision rule $d_{US}^j (h|P_{US}, H^j, \Theta^j)$ for the US. Simulate the model (as in

Section 4) to obtain predictions regarding health. Compare simulated to actual data using a distance function $L\left(H^j|d_{US}^j(h|P_{US},H^j,\Theta^j)\right)$ and minimize this function such that the distance between predicted and actual data is minimized. H^{j+1} is the parameter vector that minimizes $L()$ conditional on $d_{US}^j(h|P_{US},H^j,\Theta^j)$.

3. Given H^{j+1} and Θ^j, solve the model to obtain the decision rules $d_i^{j+1}(h|P_i,H^j,\Theta^j)$ for each country i. Simulate the model to obtain a set of predicted absence rates for each country, and evaluate a distance function $K(\Theta^j|H^{j+1},P_1,...,P_I)$ that compares the predicted moments to data. Θ^{j+1} is the parameter vector that minimizes $K()$ conditional on H^{j+1}. Repeat the steps 2 and 3 until $H^{k+1}=H^k$ and $\Theta^{k+1}=\Theta^k$.

Moments from data and the model's predictions Center For Disease Control (CDC) publishes yearly surveys (BRFSS) of self-reported health status in the US. Similar surveys are published in Europe by Eurostat, but these are less detailed, which is why the US data are used for calibration. A summary of self-reported health statistics used, including data sources and the questions ask to the respondents, are provided in the appendix. From these data I construct six moments which I use to calibrate the six health parameters H using the iterative procedure described above. These moments and the simulated model analogues are summarized in Table 2. *I* is the share of days the respondents report to be unhealthy. The model analogue is the fraction of workers with $h<h^P$. *II* is share of days the respondents report to be limited from normal activities by health problems. The model analogue is the fraction of workers with $h<h^W$. Moments *III, IV,V,* and *VI* concern the persistence of health. *III* and *IV* are the share of the respondents with zero unhealthy or activity limited days last month. Since each period lasts one week, the model analogues of these moments are the fraction of simulated agents with $h>h^P$ or $h>h^W$ in four consequtive periods. *V* and *VI* are the fraction of workers with more than 14 unhealthy or activity limited days last month. The model analogues are the fraction of simulated agents with $h<h^P$ or $h<h^W$ for at least 2 out of 4 consequtive periods.

Table 2

Moments for calibration

Health data

	Share of working pop. with:	Condition	Data	Model
	Good to excellent health	$h > h^P$	0.85	0.75
I	Unhealthy	$h \leq h^P$	0.15	0.20
II	Activity limited	$h \leq h^W$	0.03	0.05
III	0 unhealty days last month	$h_{t-4} > h^P \ \forall t = 0, .., 3$	0.52	0.66
IV	0 activity lim. days last month	$h_{t-4} > h^W \ \forall t = 0, .., 3$	0.84	0.91
V	>14 unhealthy days last month	$\sum_{t=0}^{3} I\left(h_{t-4} < h^P\right) \geq 2$	0.12	0.23
VI	>14 activity lim. days last month	$\sum_{t=0}^{3} I\left(h_{t-4} < h^W\right) \geq 2$	0.02	0.05

Absence data

Country	Data	Model	Country	Data	Model
Australia	0.0359	0.0320	Italy	0.0259	0.0356
Canada	0.0294	0.0339	Norway	0.0736	0.0734
Denmark	0.0385	0.0327	Switzerland	0.0500	0.0331
Finland	0.0355	0.0361	UK	0.0362	0.0320
France	0.0357	0.0339	US	0.0214	0.0317
Germany	0.0771	0.0548			

Data sources: OECD Health data 2006, Statistics Norway, CDC

A few remarks regarding the fit of the model are worth making. First, despite as much as 13 parameters, the model is not very flexible. Preference and policy parameters are only allowed to influence the decision rule ("up" and "down") and any "twist" in the health parameters will typically shift all countries' outcomes in the same directions. Hence, comparing the fit from a structural model like this with a fully flexible reduced form econometric model makes no sense. It is like comparing apples and pears. In my view, the health moments are captured reasonably well, even if it is far from perfect. One should keep in mind that this is a model where all individual's are assumed to be identical (apart from the realized health shocks). Other studies of absenteeism have documented that high absenteeism often is concentrated among few workers, indicating that the underlying health process is heterogeneous across people (see e.g. Markussen et.al 2009). The level of ambition for how well such a theory model can explain real world data should thus not be set too high. Inclusion of individual specific components (unobserved heterogeneity) would clearly improved the predictive power of the model, but it would probably also have made the model less useful for cross country comparisons as country specific differences are likely to be captured by such unmodelled "catch-all effects".

Second, most countries are predicted to have similar absence rates. In the data, there are two outliers, Norway and Germany. The model explains the absence level in Norway but is less able to explain the sick-leave rate in Germany. The reason is related to the high unemployment duration which feeds into the probability of finding a job when unemployed. Hence, in the model, German workers are disciplined by the fear of becoming unemployed since unemployment are expected to be (very) long lasting. One explanation why the model fails to explain the high German sick leave may be that unemployment duration is a particular poor measure for the probability of finding a new job in Germany. Unemployment in Germany is highly persistent and average unemployment duration may poorly reflect expected unemployment duration for workers with a recent employment history.

The calibrated parameters The resulting parameter values are presented in Table 3. These are the ones that will be used in the policy experiments below. Notice that the health parameters h^W and h^P corresponds to the Case 1 in the simulation exercise from Section 4. The value of α^H indicates that roughly 22% of the gap up to h^P are each week closed when restitution is chosen. The health shock parameters refer to a Pareto distributed shock and are thus not directly comparable to the parameters used in Section 4, where ε was assumed to be log-normally distributed. The coefficient for risk aversion, $\theta = 1.53$ is within the lower range of what is commonly used in the literature. The rate of intertemporal substitution $\beta = 0.99$ corresponds to yearly discounting of 0.62, which is very low. One reason for this can be that the agents are solving a somewhat short-run dilemma where outcomes seldom have effects lasting for years. The parameter values for the utility of leisure and health indicates that leisure is much more valuable to the agent when health is poor than when health is good.

Table 3

Calibrated parameter values

Explanation	Calibrated value	
Constant relative risk aversion	θ	1.53
Inter-temporal rate of substitution	β	0.99
Utility of leisure	ξ	2.85
Utility weight on leisure and health	φ	0.39
Compl. between health and leisure	ϕ	1.14
Common job-security param.	κ_0	0.01
Country specific job-security param.	κ_1	0.05
Long-term health of non-working	h^P	99.17
Threshold for work being unhealthtful	h^W	50.84
Speed of restitution when working	α_W	0.4218
Speed of restution when absent	α_H	0.2154
Mean of pareto distr. health shocks	μ	3.1028
Variance of pareto distr. health shocks	σ^2	0.0971
Earnings (constant), not calibrated	w	10

5.3 Computational policy experiments

The main advantage of structural models over reduced form models is the possibility of conducting artificial policy experiments. Clearly, computational policy experiments are not at all as robust as real world policy experiments. The good thing however, is that once the model is parameterized, a number of "experiments" can be conducted at zero cost and in the matter of few minutes. In this section, two such experiments are carried out. These are: (i) changes in sickness benefits in the US, and (ii) changes in sickness benefits in Norway. The experiment is simply that the model is solved and simulated for different values of these policy variables while everything else is kept constant.

The aim of such an exercise is to use the model to suggest optimal policy. It is important to remember that this model is partial. It describes effects of some labor market policies on health on sick leave - nothing else. These predictions are necessarily made conditional on the model, the calibrated parameter values and the other policy variables that is kept constant, or not included, in the simulation exercise. Furthermore, in a general equilibrium setting, other mechanisms would interact with the ones in the model and the conclusions drawn could have been different. Most important is probably interactions between other social insurance schemes such as disability pension, early retirement programs and unemployment insurance. For a more complete analysis of the effect of changes in sickness benefits, the model should also include these states. Such an extension could be an interesting prospect for future work.

The parameterized utility function can, together with the simulated data for health and absenteeism, be used to find agents' expected utility for each policy. For this to be meaningful, a balanced-budget restriction is imposed on the public budget. This restriction is simply that the costs of sickness insurance are tax financed and tax income must equal total sickness payments. This makes the tax rate a function of sick leave. Each agent does however not take this into account when solving the utility maximization problem in (13) since utility is maximized *given* prices and taxes. Two different calculations of expected utility are provided, one in which there is no efficiency loss from taxation, and one where this loss is as high as 40 percent. To calculate expected utility from the simulated data, these data are used as a cross-sectional dataset containing one observation for each of the $R = 10000$ simulated agents. Each of these R observations contain all three arguments in the utility function, h, l, c. Expected utility is thus simply the average utility across these R agents, when taxes are taken into consideration. Taxes are assumed to be proportional to income and all agents pay taxes regardless of whether they work or are absent, i.e. non-absent workers pay tw while absent workers pay btw. If γ is the fraction working (not on sick leave), the proportional tax rate that keeps the budget balanced is then given by $t^* = b\left(1-\gamma\right)/\left(\gamma + b\left(1-\gamma\right)\right)$. Expected utility is given by (14).

$$\widehat{EU\left(P\right)} = \frac{1}{R}\sum_{r=1}^{R} u\left(c_r, b_r, l_r\right) \tag{14}$$

Experiment 1: Optimal sick-leave benefits in Norway Norwegian employees are granted full wage replacement during sickness, and sick leave is higher than in most countries. This experiment investigates the effects on sick leave, health, and expected utility from a change in the Norwegian sickness insurance scheme. While the other Norwegian policy variables (b^U, p, EPL) are held constant, the model is solved and simulated 11 times for $b = \{0, 0.1, ..., 1\}$.

Panel (a) in Figure 5 displays the outcome of the individual decision making problem (13) - the decision rule. Note first that in the case of $b = 1$, the decision rule is above the one that maximizes health h^*, as the agent chooses leisure over health improvements and improved job-security. When b is reduced, the decision rule falls steeply, and when $b < 0.4$ the decision rule is below h^W. An interesting detail is that the decision rule is not monotone in the level of sickness benefits. The reason is that increased sick-leave benefits has two competing effects on the individual. First, conditional on being employed, sick leave becomes more attractive. However, at the same time, introducing sick-leave benefits makes employment more attractive to unemployment. Consequently, keeping the job becomes more valuable when sick-leave benefits are introduced which is why the decision rule decreases when sick-leave benefits increase from 0 to 0.1.

Panel (b) displays the predicted sick-leave rate as a function of sick-leave benefits. We see that sick leave is unaffected up to $b = 0.4$. As b increases further, sick leave increases at an increasing rate. Panels (c, d) decompose the changes in sick leave into changes in the incidence rate og changes in spell duration. For $b \leq 0.7$ the incidence rate is weakly decreasing as b increases while spell duration is weakly increasing. Hence, behind the apparently unchanged sick-leave rate, the composition of sick leaves changes. As b increases, sick-leave spells becomes longer but also less frequent. When b exceeds 0.7 both duration and the incidence rate increases sharply which explains the steep increase in the sick-leave rate.

Panel (e, f) displays how health changes with b. Higher sick-leave benefits are predicted to increase public health and reduce health inequalities. When subjected to less pressure, workers allow themselves longer recovery periods from sickness.

Panel (a) in Figure 6 illustrates the trade-off between sick leave and health faced by policy makers, and draws a connected scatter plot between the feasible outcome combinations of sick leave and health. A policy maker will typically prefer allocations towards the north-west corner, minimizing sick leave and maximizing health. The figure illustrates however that these two ambitions are conflicting when deciding the optimal level of sick-leave benefits. In addition, and outside this model, there is obviously a question

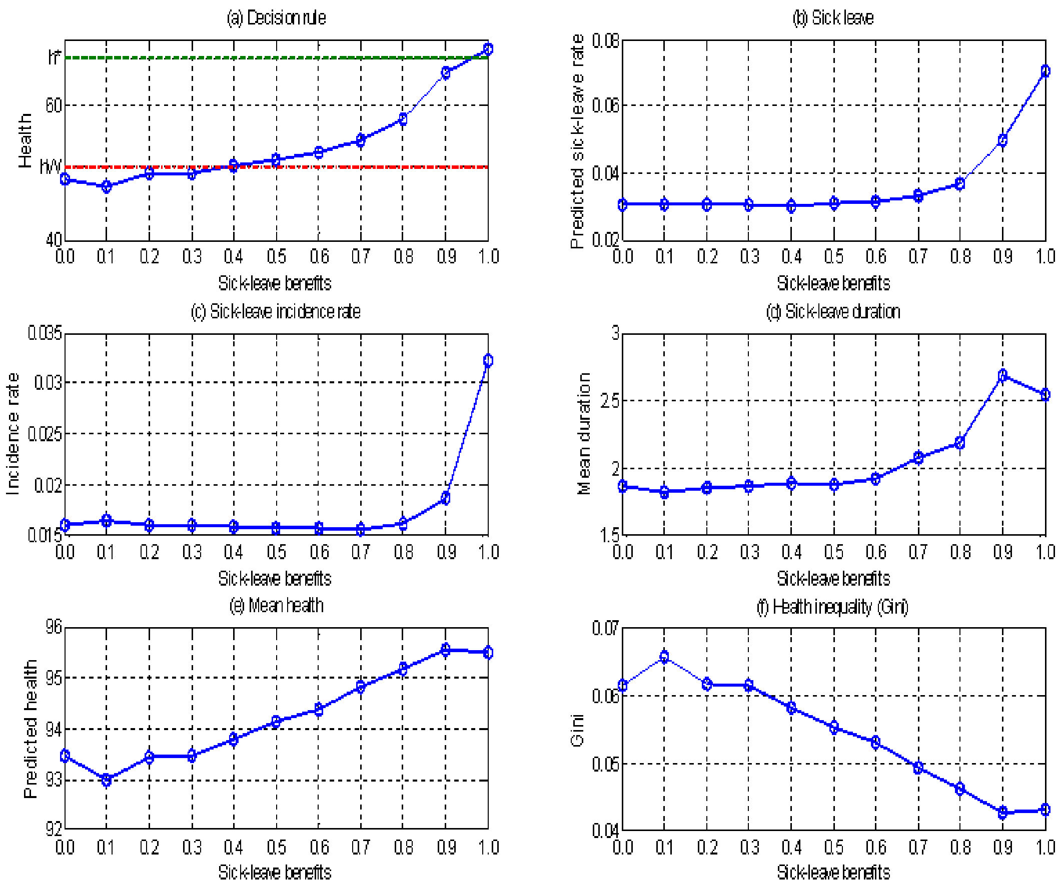

Figure 5: **Predicted consequences for sick leave and health from changed sick-leave benefits in Norway.** Using the calibrated model and keeping other Norwegian policy variables unchanged, the predicted outcomes from changed sick-leave benefits can be evaluated. Panel (a) displays the outcome of the decision making model, the decison rule, which is such that workers choose work if health is above and sick leave if health is below. Panel (b) displays the predicted sick-leave rate as sick-leave benefits are changed from zero to 100 percent. Panels (c, d) decomposes these changes in the incidence rate for sick leave and mean spell duration. Panel (e) show the corresponding effects on predicted health and panel (f) draws the gini coefficient for health measuring effects on health inequality.

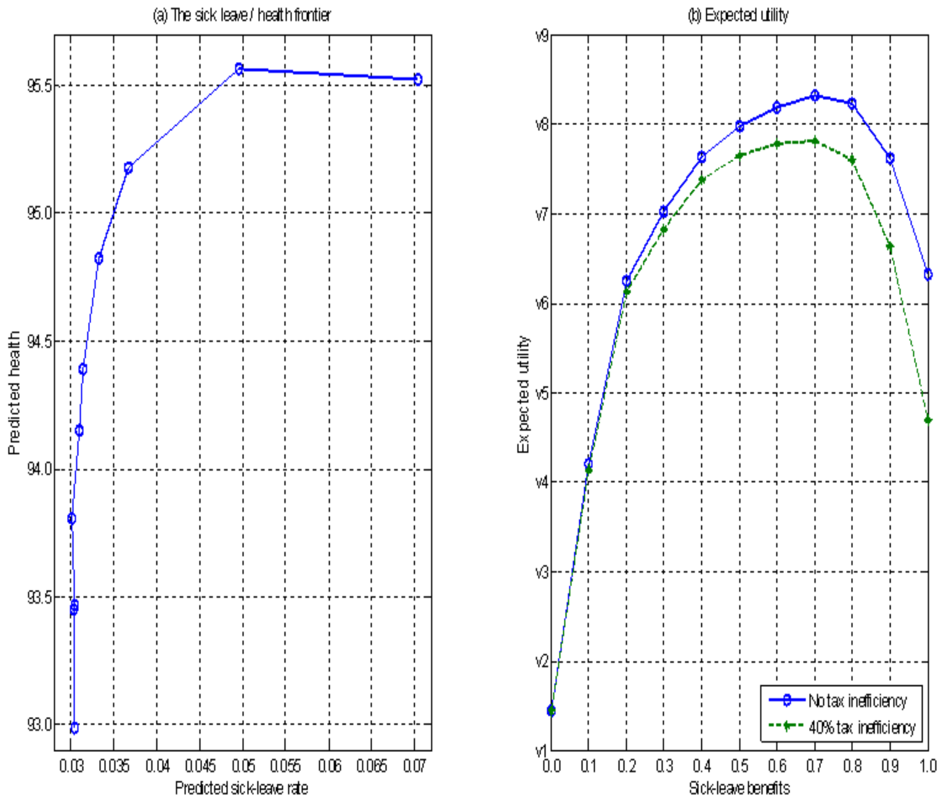

Figure 6: **Optimal sick-leave benefits in Norway.** Using the calibrated model and keeping other Norwegian policy variables unchanged, the predicted outcomes from changed sick-leave benefits can be evaluated. Panel (a) draws the combinations of predicted sick leave and health "available" for policy makers. Panel (b) displays expected utility or welfare as a function of sick-leave benefits for two different assumptions regarding tax inefficiencies.

of economic equity that also should be included in such a discussion. Panel (b) shows expected utility or welfare, based directly on the parameterized preferences and the simulated outcomes. Regardless of whether we consider fully efficient, or rather inefficient taxation, strictly positive sickness benefits turn out to be optimal. The optimal replacement rate is around 0.7. Such a reduction in sick-leave benefits are predicted to reduce sick leave substantially while the corresponding effects on health are modest. Taken at face value the model's results show that Norwegian workers are under too little pressure because of the generous social insurance scheme.

Experiment 2: Optimal sick-leave benefits in the US Figure 7 displays the predicted outcomes for different levels of sickness benefits in the US. The results are fairly similar to the ones regarding Norway, but there is a least one interesting difference. In the case of $b = 1$, the sick-leave rate in US are predicted to almost 5 percent. In Norway, it is above 7 percent. The reason is that US workers are subjected to higher pressure, also conditional on the level of sick-leave benefits, since job-security is substantially lower in the US. The fear of becoming unemployed is thus disciplining workers more in the US than in Norway which has stronger employment protection legislation. Panel (a) displays the predicted sick-leave rate as a function of sick-leave benefits. We see that sick leave is unaffected (weakly decreasing) up to $b = 0.5$.As b increases more, sick leave increases at an increasing rate. Panel (b) displays mean health as a function of sick-leave benefits. We see that such benefits are predicted to increase public health. When subjected to less pressure, workers allow themselves longer recovery periods from sickness. Panel (c) draws a connected scatter plot between the feasible outcome combinations of sick leave and health. The last panel (d), shows expected utility or welfare based directly on the parameterized preferences and simulated outcomes. Regardless of whether we consider fully efficient, or rather inefficient taxation, a strictly positive sick-leave benefit scheme turn out as optimal. The optimal replacement rate is, as in Norway, around 0.7. Hence, US workers are subjected to more pressure than necessary to avoid problems with moral hazard.

Limitations of the analysis First, and probably most important, the assumption of no savings will tend to exaggerate the effect of sick-leave benefits on the decision rule. If workers were able to save they could self-insure against short term sick leave. Such consumption smoothing would be preferred and would have changed the model's predictions. However, self-insurance still implies that sick leave is paid by the individual when sick-leave benefits not fully cover lost earnings and would consequently still be a relevant policy instrument. Second, there is no signalling costs of sick leave in this model. The only source of long-term costs of sick leave is the increased probability of being unemployed. Other studies have shown that being on sick leave has substantial costs in the long run because it affects future earnings and carreer prospects (see e.g. Ichino and Moretti, 2009; Hansen, 2001; Markussen, 2009). Third, this model is mainly a model of

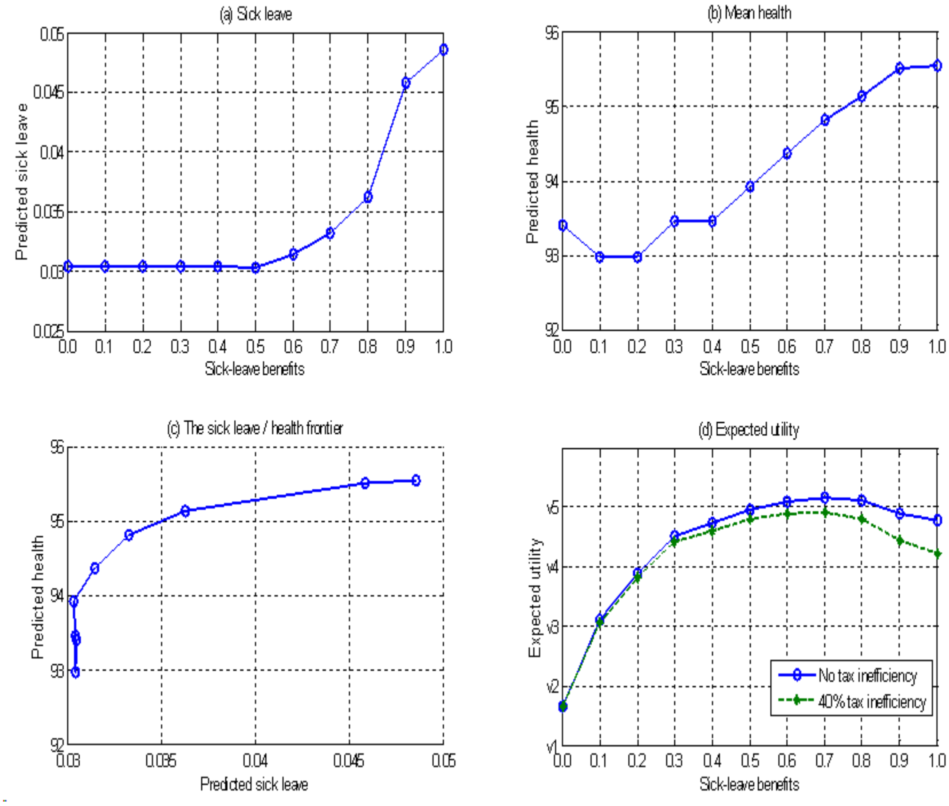

Figure 7: **Optimal sick-leave benefits in the US.** Using the calibrated model and keeping other US policy variables unchanged, the predicted outcomes from changed sick-leave benefits can be evaluated. Panel (a) displays the predicted sick leave as sick-leave benefits are changed from zero to 100 percent. Panel (b) show the corresponding effects on predicted health. Panel (c) draws the combinations of predicted sick leave and health "available" for policy makers. Panel (d) displays expected utility or welfare as a function of sick-leave benefits for two different assumptions regarding tax inefficiencies.

short-term health problems. There is no illness in this model from which agents do not recover. A more realistic model would also incorporate permanent health shocks. Fourth, short-term illnesses are often infectious. Going to work when ill has then an externality since it increases the risk of others to become ill. This mechanism is not included in the model, but if it was it would make the case for paid sick leave stronger. Finally, moving from infinite to finite horizon would make it possible to study the effects of aging and how agents change behavior as they approach the retirement age. Typically sick leave is the highest among these workers. Dealing with these limitations are all interesting prospects for future research.

6 Concluding remarks

Sick leave is related to health. This paper argues that health is also related to sick leave. The mechanism through which this relationship is hypothesized is that working when sick may be unhealthful. When such a mechanism is incorporated in a model of labor supply, this model shows that policy makers face conflicting interests when deciding on the optimal level of sick-leave benefits. In this model, sick-leave benefits tend to increase sick leave as it makes workers stay home for health levels they otherwise would have worked. On the other hand, allowing oneself to recover from illness before returning to work is good for health.

The results of this paper is that optimal sick-leave benefits neither are zero not 100 percent. Having no sick-leave benefits is not optimal because the increases in sick leave from more generous sick-leave benefits are small compared to the gains in health. Nor is full wage replacement during sickness optimal. By reducing sick-leave benefits somewhat, sick leave falls substantially while health are kept almost unchanged. A calibration exercise confirms these intuitions. Based on the calibrated model, the optimal amount of wage replacement during sickness is around 70 percent.

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7 Appendix: details regarding Section 5

Solving the model numerically The state space is discretized such that there is a grid with 100 levels of health and 5 levels of job-security. The model is thus solved for each of these 100×5 state combinations. Expected utilities are calculated by interpolating between these state combinations. 5 levels of job-security (with sufficiently distance in between them) seem sufficient for the problem to be meaningful for an agent with job-security in the middle grid point. Since I only study this agent's decisions, the decision rule presented is a function of health, conditional on job-security.

To only focus on the decision rule for agents with a particular level of job-security will also affect the simulations. In other work I have tried to allow for job-security to enter in the decision rule and incorporate this in the simulations. This generates some interesting features giving some insight but it is also likely to provide unlikely features such that workers with (very) high job-security always shirk since the cost is almost zero. (They go in and out of sick leave to keep job-security on their preferred level). However, the aggregate predictions seem fairly unaffected and I do not belive that any of the results in this paper would have changed substantially by including π in the decision rule. Including $d(h, \pi)$ in the simulations would also required a much larger state space for π which would have made the calibration procedure less tractable.

Policy variables Table A1 lists the policy variables used to solve the model. These originate from different sources (all specified in the Table's notes).

Table A1

Labor market policy and sick leave					
Country	b	b^U	$1/p$	EPL individual dismissal	Absence rate
US	0	0.58	13.9	0.07	0.0214
UK	0.22	0.2	60.2	0.46	0.0362
Canada	0.63	0.63	19.4	0.55	0.0294
Australia	0.29	0.29	12.7	0.63	0.0359
Finland	0.75	0.59	55.6	0.9	0.0355
France	0.62	0.8	69.9	1.03	0.0357
Denmark	0.52	0.62	49.5	0.61	0.0385
Switzerland	0.54	0.72	67.0	0.48	0.0500
Germany	0.94	0.6	79.0	1.12	0.0771
Norway	1	0.66	18.4	0.94	0.0736
Italy	0.75	0.38	35.4	0.74	0.0259

Sources: (1) replacement rates for sickness and unemployment from Scruggs (2004), "sick" and "ue", mean 96-01, (2) unemployment duration, DK, ITA,UK,GER: from Tatsiramos (2006) - Unemp.duration for benefit recipients, SWI: from OECD, mean across men and women 00-01, total pop., remaining countries: mean across men and women, 00-01, aged 25-64. (4) Indicator for EPL individual dismissal, OECD 2003. (5) Absence data from OECD Health data 2006 and Statistics Norway.

Self-reported health Table A2 presents self-reported health data for Europe and the US. Center For Disease Control (CDC) publishes yearly surveys (BRFSS) of self-reported health status for the US, and Eurostat publishes similar surveys for Europe. Some of these data (displayed in Table 2) are used to calibrate the model. The US data are chosen for calibration because they contain information also about *health dynamics* such as the share of population with zero unhealthy days last month. The data for US and Europe are fairly similar along those dimensions we can observe, making it more probable that the US data are representative also for Europe.

Table A2

Self-reported health status

The table shows data for self-reported health from CDC (US) and Eurostat (Europe).

	1	2	3	4
Self-rated health status[4]	US working[5]	US inactive[6]	EU working[7]	EU inactive[8]
5 (best)	.270	.198	.199	.117
4	.375	.307	.515	.356
3	.276	.338	.226	.332
2	.069	.127	.049	.140
1 (worst)	.009	.031	.011	.054
Health last month:				
Unhealthy days[9]	.147	.253	.112[10]	.217[11]
Activity limited days	.03	.09	.035[12]	.167[13]
Share of pop. with...				
zero unhealthy days	.516	.417	-	-
zero activity lim. days	.840	.742	-	-
> 14 unhealthy days	.122	.239	-	-
> 14 activity lim. days	.022	.085	-	-

In the surveys for the US, CDC asks the the respondents the following questions:

1. Self-rated health: *Would you say in general that your health is excellent, very good,*

[4]The scales used by CDC and Eurostat differ somewhat. CDC: 5 = Excellent, 4 = Very good, 3 = Good, 2 = Fair, 1 = Poor. Eurostat: 5 = Very Good, 4 = Good, 3 = Fair, 2 = Bad, 1 = Very Bad.

[5]Respondents "Employed for wages", mean 1993-2001, source: Behavioral Risk Factor Surveillance System, Center for Disease Control (BRHSS-CDC).

[6]Respondents unemployed less than 1 year, BRFSS-CDC 1993-2001

[7]Data for EU-15 by Eurostat, Self-perceived health by work status, 1998

[8]Data for EU-15 by Eurostat, Self-perceived health by work status, 1998

[9]BRFSS-CDC, 1993-2001, Mean number of overall unhealthy days last 30 days, divided by 30.

[10]Formulation here is: "To some extent hampered in daily activities", Eurostat 1998.

[11]Formulation here is: "To some extent hampered in daily activities", Eurostat 1998.

[12]Formulation here is: "Severely hampered in daily activities", Eurostat 1998

[13]Formulation here is: "Severely hampered in daily activities", Eurostat 1998

good, fair, or poor?

2. Physically unhealthy days last month: *Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good?*

3. Mentally unhealthy days last month: *Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?*

4. Activity limitation: *During the past 30 days, for about how many days did poor physical or mental health keep you from doing your usual activities, such as self-care, work, school, or recreation?*

Minimizing the functions $L()$ and $K()$ It turns out that minimizing L and K, which is the objective functions used to determine the parameters H and Θ, is hard as they often tend to be piecewise constant. The reason is simply that small changes in one parameter not always imply large enough behavioral changes to be captured by the moment used. It has consequently been necessary to apply a smoothing routine for L and K. The basic idea is easy illustrated by using the first health moment, $\hat{m}_1$, as an example. In the simulated dataset, $\hat{m}_1$ is simply the *share of the popluation* with $h < h^P$, i.e. $\hat{m}_1 = \frac{1}{R}\sum_{r=1}^{R} I\left(h_r < h^P\right)$. The "smoothed moment" $\hat{m}_1^s$ is instead the *probability* of $h < h^P$. I assume $h - h^P$ to be distributed normal with zero mean and variance σ^s. Hence, $\hat{m}_1^s = \frac{1}{R}\sum_{r=1}^{R} F\left(h_r - h^P|\sigma^s\right)$. σ^s is then the "smoothing factor". As $\sigma^s \to 0$ $\hat{m}_1^s \to \hat{m}_1$. For $\sigma^s > 0$ the function L is smoothed and optimization techniques involving gradients can be applied.

For a given $d(h)$, H is found by the following iteretative scheme: Start out with a vector H and a smoothing factor $\sigma_n^s > 0$ and minimize $L^s(H) = [\mathbf{m} - \hat{\mathbf{m}}^s]'[\mathbf{m} - \hat{\mathbf{m}}^s]$. Reduce σ^s such that $\sigma_n^s > \sigma_{n+1}^s > 0$ and minimize $L^s(H)$ again until convergence. Repeat this routine until σ_{n+k}^s is sufficiently small for $\hat{m}_i^s = \hat{m}_i$ $\forall i = 1,..,6$.

A major caveat for this kind of optimization is to distinguish global from local maxima. With 13 parameters and a full structural model that must be solved and simulated for each change in one of the parameters it is complicated and extremely time consuming to search through the entire parameter space. Using a combination of gradient search methods and grid search based on simplex methods (functions *fminunc* and *fminsearch* in Matlab) I have made attempts by starting the problem at different parameter vectors H and Θ and compare the maxima at which it ends. However, there is no method I am aware of nor capable to employ that can ensure that the parameters displayed above are the ones that truly minimizes the objective functions L and K. This is the main reason, toghether with several identification issues, that I consider the model to be calibrated, but not estimated.