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**Informal Payments for Health Care and their Implications on
Patient Welfare**

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Abstract

Corruption in the healthcare sector is a widespread problem in many countries. Empirical research has shown that petty corruption is especially endemic in healthcare, perhaps due to the importance of health to human beings. In this thesis I will study the transmission of informal payments for health care between patients and physicians and its effect on patient welfare, taking social norms about corruption into account. A Monte Carlo estimation is used to estimate patient welfare and health outcomes of an iterated two-stage game where a new physician-patient pair meets in every stage of the game. I will simulate three cases. A benchline case where informal payments are non-existing and two cases where informal payments exist, one where the social norm is not to pay an informal payment for health care and one where the social norm is to pay an informal payment for health care. In the model, patients can be severely ill or mildly ill and be able to borrow for informal payments or not. The results show that even if traditional measures of welfare go down as corruption goes up, health outcomes improve when informal payments for health care are introduced and increase when patients are mildly ill, physicians are forward looking and have only one shot at offering patients a contract (i.e. no bargaining takes place).

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1

Introduction

Despite the complexity of healthcare systems they all boil down to the interaction of physicians and patients, more or less constrained by diverse regulations. The meeting of physicians and patients is the root of several sources of inefficiency that characterize the health sector. Firstly, there is an inherent uncertainty about the “good” traded between physicians and patients, i.e. health care, since both diagnostics of illnesses and treatment results are uncertain to a certain degree. The occurrence of wrong diagnosis depends on which body part or organ is studied, but, for example, only 30% of diagnoses general practitioners made about abdominal pain were correct (Morelli, 1972). Treatment uncertainty depends heavily on the disease in question, cancer treatments, for example, often have uncertain treatment results while bacteria caused pneumonia almost certainly is curable with antibiotics. Secondly, the meeting of physicians and patients is a prime example of an encounter characterized by asymmetric information since physicians have a large informational advantage over patients when it comes to diagnosis, available treatments and treatment results. Thirdly, due to the nature of health care, suppliers of health care often have a considerable market power, especially when the private health sector is small or absent.

In addition to the above mentioned sources of inefficiency, corruption, defined as “the misuse of public power for private gains” Rose-Ackerman (1999), is also a candidate for causing inefficiency when physicians and patients meet. Studying micro-level corruption, the health sector turns out to be prone to corruption. For example, empirical research on corruption in Bangladesh has shown that 42% of

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respondents to a survey about corruption had encountered some type of petty corruption¹ within the health sector during the last 12 months (the survey was executed in 2007) while 35% of respondents had encountered some type of petty corruption within the educational sector. The difference between the sectors becomes even larger when the occurrence of bribery is studied; 21.7% of all respondents had encountered bribery within the health sector while only 6.9% of all respondents had encountered bribery within the educational sector (Knox, 2009). Although Knox does not define bribery or bribes in his paper, a general view on bribes is that they are illegal side-payments made in exchange of service/good from a public official (private-to-private corruption, including bribing, also exists, but is less discussed). The briber can be entitled to the service/good exchanged by law but still has to pay, or he can pay for additional or better service/good than entitled to by law. One explanation for the high occurrence of bribery in the health sector is that since money flow from the government into the health sector is low in corrupt countries², bribes from patients to physicians are needed in order to maintain an acceptable level of health care. This explanation is also coherent with the theory that corruption trickles down to the people when it exists in high places of the society. Another possible explanation is the importance of health to human beings, especially when the health service traded is a question of life rather than death for the patient receiving it.

In the sections to come, the term bribe will not be used as is done in Knox (2009), since its meaning implies an illegal activity. Instead, following Cohen (2011), the term informal payment for health care (IPHC) which includes semi-legal and legal informal payments that take place outside the official payment channels in addition to the illegal ones (bribes), will be used.³ Also, following Cohen (2011), social norms about corruption are taken into account when discussing IPHC. It is clear that in a society where paying extra for health care is

¹Petty corruption refers to small scale corruption such as citizens bribing public officials

²Research has shown that corrupt government prefer to channel money flows to sectors where large, special investments (which are well suited for rent seeking) are common. The military sector is a prime example of such a sector. (See e.g. Gupta et al. (2001))

³Informal payments for health care are for example tax-deductible in Hungary (Gaal et al., 2006) and Poland (Shahriari et al., 2001) and can thus not be seen as illegal.

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the norm or even legal, the ethical cost of IPHC (i.e. bad conscience from offering/accepting IPHC) is strongly linked to the socially accepted level of IPHC, whether it is zero or not.

As sources of inefficiency in health care, asymmetric information and uncertainty have been studied extensively, often from a principal-agent perspective,⁴ as discussed by e.g. Dranove and White (1987) and Mooney and Ryan (1993).⁵ The approach is designed to handle situations that include asymmetric information and uncertainty such as the interaction of physicians and patients. However, unlike the standard principal-agent model, the outcome of health care is non-contractible in the sense that the health status of patients after treatment is not directly observable,⁶ neither for the patient nor for the physician (Mooney and Ryan, 1993). When applying the principal-agent model, the physician is modeled as the agent that both decides on the patient's (the principal's) demand for health care as well as supplies the demanded amount of health care to the patient.

In contrast to asymmetric information and uncertainty as sources of inefficiency in the meeting of physicians and patients, there exists little research on the inefficiency caused by informal payments, IPHC, when physicians and patients meet. The purpose of this thesis is to make an attribute to this field of the health economics literature. More precisely, the effect of IPHCs from patients to physicians on patient welfare and health outcomes, taking social norms about corruption into account will be studied. A benchline case where IPHCs do not exist, a case where IPHCs exist but the social norm is not to pay one and the case where the social norm is to pay a certain IPHC will be studied and mutually compared.

⁴The principal agent approach is theoretic model of the encounter of an agent and a principal where the agent has informational advantages over the principal. The principal assigns a job to the agent where the agent can use his informational advantages to maximize his own utility on the cost of the principal's utility.

⁵The principal-agent model has also been applied to e.g. the meeting of physicians and providers (the state) and physicians and pharmaceuticals.

⁶The physician could e.g. withhold information about the patient's health status in order to pretend that the result of the treatment is better than it really is, and the patient could e.g. claim that he doesn't feel better.

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The model presented here is an iterated two-stage game where a new pair of physician and patient meets in each iteration of the game (i.e. no information is transmitted between stages of the game). Using a Monte Carlo method where the patient's wealth and initial health status as well as the corruptibility of both the physician and the patient are randomly drawn from a given distribution, aggregate patient welfare is calculated according to several welfare functions. For all three cases, the benchline case, the case with $IPHC_{norm} = 0$ and the case with $IPHC_{norm} > 0$, two scenes will be studied: A scene where health care is necessary to save the patients' life and a scene where the patients will survive, even without a treatment. Finally, the patients' possibility to borrow money for paying IPHC when the demanded amount exceeds their wealth will be varied.

In chapter 2, a review of the existing literature on the subject will be given and the modeling approach used here motivated. In chapter 3, the model is introduced. In chapter 4, simulations and results are presented. In chapter 5, the robustness of the results is investigated. Chapter 6 concludes with a discussion of the results, possible modifications and extensions of the model and policy implications.

2

Literature review and motivation of my approach

As already mentioned, asymmetric information and uncertainty as sources of inefficiency in the physician-patient encounter have been widely discussed, most often using the principal-agent approach (see e.g. Dranove and White (1987) and Mooney and Ryan (1993)), while there exists little research on the welfare and efficiency effects of corruption in the form of IPHC between patients and physicians. Vaithianathan (2003) is one of the few papers discussing this topic. There, the author studies a social planner's objective to minimize health care costs given physicians' incentives to choose the appropriate treatment for each patient type when collusion between patient and physician is allowed (compared to a collusion-free benchmark model). Vaithianathan finds that when patients are well-informed, the cost of inducing a collusion free scheme is high. She also shows that when physicians have all the bargaining power (monopoly) and patients have high willingness to pay for health care, the collusion robust scheme is preferred by the buyer.

2.1 Social planner and physician market power

In the model developed in Vaithianathan (2003), it is the social planner's cost that is minimized while social efficiency in the form of optimal health outcome is only included as a constraint in the optimization problem. In other words, the social

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planner minimizes his costs under the constraint that the health outcome fulfills an exogenously given standard (i.e. correct treatment for all patients). The social planner does this by economically punishing physicians who give wrong treatment to patients.¹ This way of treating the social planner's problem in health care is related to the vast literature on paying schemes for physicians. Different schemes, e.g. capitation payments², supply-side or demand-side cost sharing³ etc. yield different incentives for physicians and thus different outcomes when it comes to the cost of health care for the social planner and health outcome as discussed in e.g. Ellis and McGuire (1993). Another approach to the social planner's problem in the health sector is to let the social planner maximize patient welfare, eventually given some cost constraints and/or constraints due to physician behavior and incentives.

Contrary to Vaithianathan (2003), it will be assumed here that the social planner is inactive in the sense that he does not have the power to manipulate the incentives of patients and/or physicians through e.g. supply- or demand side cost sharing. The physician payment scheme as well as patient's cost scheme and insurances will be exogenously given. As a consequence, the focus of the model will solely be on the effect of IPHC on the behavior of physicians and patients in a fix setup of the health care sector.

Whichever approach is used to tackle the social planner's problem, one must decide on how the bargaining power is divided between the physician and the patient. In the literature that uses the principal agent approach to explain the physician-patient meeting, it is common to assume that the physician has monopoly power (Dranove (1988) McGuire (1983), Gaynor (1995)). This corresponds to the case when patients do not have the private health sector as an exit

¹In Vaithianathan (2003), the social planner's objective is maximized when severely ill patients get high intensity treatment and mildly ill patients get low intensity treatment. It is however the wish of both physicians and all patients to offer/receive high intensity treatment, irrespective of the patient's condition since it maximizes their utility.

²Capitation payments are a fix payment per patient treated, irrespective of the treatment used.

³Supply-side cost sharing refers to the case when physicians pay a part of the treatment cost, together with the social planner, while demand-side cost sharing refers to the case when patients pay a part of the treatment cost. In both cases the goal of the paying scheme is to avoid too expensive treatments.

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option, and in addition, there is no competition between different physicians in the public sector. The bargaining power can also be modeled as being shared between physicians and patients. In McGuire (2000), the physician's monopoly is reduced by a constraint in his profit maximization that states that the patient's utility from meeting the physician and getting treatment must be at least as high as the utility the patient will get visiting competing physicians. This can correspond either to physicians in the public sector that compete with each other or to the possibility for patients to turn to the private sector with their health problem. Finally, Vaithianathan (2003) studies both the physician monopoly case as well as the case where patients have bargaining power.

In the model presented in this thesis, a traditional approach to the subject will be followed and focus is laid on the physician monopoly case. However, a twist to the traditional monopoly approach will be introduced and both the case when patients have access to financial markets and can borrow money to pay the IPHC demanded when it exceeds their wealth, as well as the case where none of the patients can borrow money will be studied. Also, the case when patients have zero reservation utility and the case when patients have non-zero reservation utility will be studied. This could correspond on the one hand to severely ill patients who almost certainly will die if not treated and thus get the utility zero if not treated and on the other hand to mildly ill patients who almost certainly will survive even if not treated. The two groups of patients could e.g. be terminal cancer patients (almost certain death) and patients with eye problems (almost certain to survive).

2.2 Social norms and ethics

Social norms about corruption are not to be confused with the level of corruption which is a widely discussed term in the economics literature. When talking about the level of corruption, authors are usually referring to indexes produced by organs like Transparency International where countries are given scores and ranked according to the perceived level of corruption in each country. These indexes are then used to do macroeconomic studies, often about the relationship between

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corruption and growth.⁴ The level of corruption has also been used in microeconomic studies, for example by Ryvkin and Serra (2012) where the authors define the level of corruption as the “probability that a randomly drawn pair of a citizen and a public official engages in a corrupt transaction” Ryvkin and Serra (2012, p. 470).

While the term “level of corruption” describes the probability (perceived or real) of corrupt activities taking place, social norms about corruption or informal payments describe the situation where corruption/informal payments are accepted as the normal behavior in society, that is, when the level of corruption is so high that almost everybody in that society engages in corruption/transfers informal payments. When this is the case, sociological theories such as Dahrendorf’s homo sociologicus (Dahrendorf, 1973) become relevant for explaining the norm-following behavior of the citizens.

Social norms and IPHC have been widely discussed in the literature on health policy, often in relation with specific countries or cultures. Cohen (2011) discusses the situation in Israel and comes to the conclusion that IPHCs are a part of a larger problem, a culture of corruption in society which he calls “alternative politics”. Also, several authors have discussed the occurrence of corruption in Eastern Europe after the fall of the Soviet Union (see e.g. Gaal et al. (2006)).

In the general economic literature, social norms and corruption have been discussed in several contexts. Mauro (2002) claims that social norms lie behind the persistence of corruption in corrupt countries, and Fisman and Miguel (2006) do an empirical study on the connection between culture and corruption. In psychological game theory where guilt is studied, an alternative view on the link between social norms and corruption is presented. Charness and Dufwenberg (2006) define guilt as the feeling a person gets when he “believes he hurts others relative to what they believe they will get”, i.e. a person feels guilt when he or she does not follow social norms when interacting with others. Balafoutas (2011) then

⁴There exist a few papers that do empirical studies in different countries in order to pin down the actual level of corruption, see for example Mocan (2004), Svensson (2003) and Swamy et al. (2001). These papers generally discuss similar topics as papers that use indexes, i.e. macroeconomic questions such as the effect of corruption on growth.

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uses these ideas to study how guilt aversion and social norms about corruption⁵ affect the level of corruption in society. Ryvkin and Serra (2012) discuss the effect on the level of corruption when corruptibility is taken to be private information for both the briber and the bribe. They find that when this is the case, the level of corruption in society is lower than when corruptibility is general knowledge.

Despite the richness of research on social norms and corruption and/or informal payments in the health policy literature and in the general economic literature, there is little to be found on the subject within health economics. By employing ideas and terms from the literature on health policy and the general economics literature and applying to the health sector, this thesis is an attempt to fill that gap. In the model, an ethical component in that relates to social norms and guilt aversion in the spirit of Charness and Dufwenberg (2006) and Balafoutas (2011) will be included. Inspired by Ryvkin and Serra (2012), the functional form of the ethical component for each patient and each physician will be made private information. The functional form decides how morally sensitive patients and physicians are to being corrupt, that is, how much disutility they get from paying IPHC that are higher than the socially accepted amount.

In the following sections, the term social norm about IPHC (or $IPHC_{norm}$) will be used for the accepted amount of IPHC in a society where the level of corruption is so high that one can say that it is the social norm to be corrupt and pay/accept an IPHC of a certain amount.

⁵Balafoutas uses the term public beliefs instead of social norms, which he defines as the bureaucrat's belief about how the public believes he is (i.e. how corrupt he is).

3

The model

3.1 Model setup

The effect of IPHC on patient welfare given the existence of social norms about IPHC will be studied for three versions of IPHC structures. In the first version, the benchline case, IPHCs are non-existing. In the second version of the model, not paying IPHCs is the social norm. However, physicians and patients are allowed to exchange an IPHC if they wish to do so. In the third version of the model, the social norm is to pay a certain IPHC, larger than zero. Again, physicians and patients can exchange an IPHC larger than the socially accepted amount.

For the benchline case as well as for the two versions where IPHCs are allowed, the scenario when patients have zero reservation utility as well as the scenario when patients have non-zero reservation utility will be studied. The two scenarios can correspond to different types of patients: Severely ill patients who will almost certainly die if not treated for their illness, and mildly ill patients who will almost certainly survive although not treated by a physician. Also, the patients' ability to borrow money for IPHC when it exceeds their wealth will be varied, such that either all or none the patients who need to borrow money do so.

The physician-patient meetings are modeled as independent two-stage games which, in a large set, form the grand game. The grand game thus is a repetition of a large number of two-stage games describing physician-patient encounters. In all of the above listed versions of the model, each two-stage game (i.e. each

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physician-patient meeting) consists of three steps, of which the first can be seen as external (act of nature) to the two-stage game: (i) Patient and physician are chosen by nature. The patient's health, wealth and corruptibility (ethical sensitivity to IPHC) and the physician's level of compassion and corruptibility are all randomly drawn. (ii) Utility is maximized. The physician then offers the patient a treatment contract according to the results of his maximization. (iii) The patient agrees or does not agree on the contract offered by the physician according to whether the utility they self expect getting from the treatment exceeds their reservation utility or, when borrowing money is impossible, whether the IPHC demanded exceeds their wealth.

The numerical value of the patient and physician utility from the treatment in each simulated physician-patient meeting is calculated. After a large number of iterations of the two-stage game, all the obtained patient utilities are used to calculate the patient welfare according to two known social welfare functions: the utilitarian social welfare function and the Rawlsian social welfare function (maximin). In addition, the utilitarian patient welfare is calculated for the top and bottom 10 % of the population (in utility) and the ratio of these two measures is studied as an indication of equity. Also, health outcome from treatment (which is an ingredient in both patients' and physicians' utility functions) is studied. Mean health of the whole sample, mean health of the top and bottom 10 % and the top-bottom ratio is studied. For all these measures, both the group of all patients and the group of patients who received treatment will be studied. Finally, physicians' effort is exited from the simulations to better illustrate the mechanisms behind the results obtained.

A Monte Carlo method is the used to estimate patient welfare. The grand game is iterated a large amount of times and the mean of all the results is taken to obtain a final numerical measure of patient welfare, health and physician effort. The values obtained this way in the versions of the model where IPHCs are allowed will then be compared to each other and to the values obtained from the IPHC-free benchmark version of the model.

All the values of patient welfare, health and effort studied are numerical values which of course have no meaning if standing alone. It is only in the comparison of

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the three versions of the model, that the numbers obtained from the simulation make sense.

In order to summarize the sequence of actions described above, figure 3.1 describes the timing of the two-stage game while figure 3.2 describes the Monte Carlo estimation of welfare and health measures of the grand game.

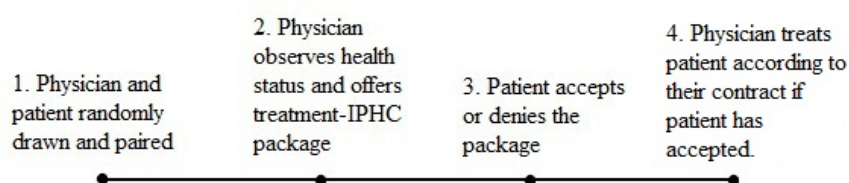


Figure 3.1: Timing in a two-stage game

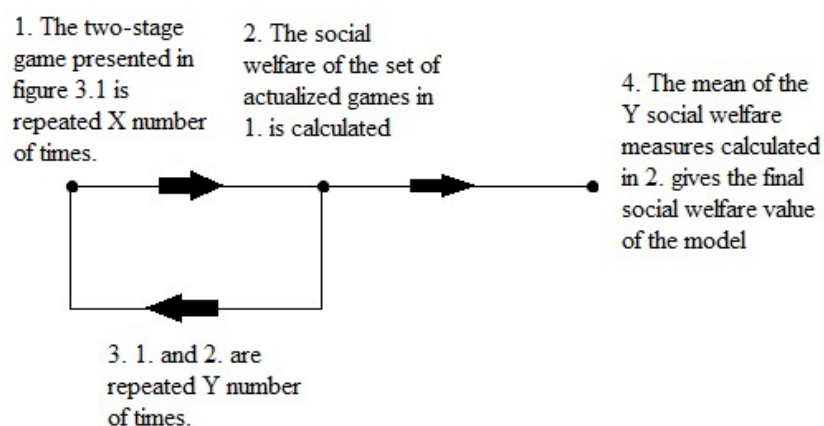


Figure 3.2: The Monte Carlo simulation of the iterated two-stage game

There are four sources of asymmetric information in the model. Firstly, it is assumed that patients do not know their initial health status. Thus, the patients' health status is private information for the physicians. Initial health status is drawn from a unimodal beta distribution on the interval $[0, 1]$.¹ Even if patients do not know their health status, they can (rightly) estimate it as bad, intermediate

¹A beta distribution is a very flexible distribution defined on the interval $[0, 1]$, depending

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or good. Patients who have initial health status on the interval $[0, \frac{1}{3}]$ perceive their own health as bad (initial health status set to $1/6$). Patients with initial health on the interval $[\frac{1}{3}, \frac{2}{3}]$ perceive their own health as intermediate (initial health status set to 0.5) and patients with initial health on the interval $[\frac{2}{3}, 1]$ perceive their own health as good (initial health status set to $5/6$). Secondly, the patients' wealth is private information and randomly drawn for each two-stage game from a unimodal beta-distribution on $[0, 1]$. Thus, physicians do not know their patients' wealth, but they estimate it when they constrain their own utility maximization with patients' reservation utility. Further, it will be assumed that physicians rightly estimate patients wealth as low, intermediate and high. Thus, all patients with wealth on the interval $[0, \frac{1}{3}]$ are seen by physicians as poor (wealth set to the value $1/6$), all patients with wealth on the interval $[\frac{1}{3}, \frac{2}{3}]$ are estimated to be averagely rich (wealth set to the value 0.5) and all patients with wealth on the interval $[\frac{2}{3}, 1]$ are seen as rich (wealth set to the value $5/6$). Thirdly, the corruptibility, i.e. the ethical sensitivity to IPHCs of patients, is private information. In the model, corruptibility is expressed by the functional form of the ethical-social norm component. For each patient and each physician, a parameter is randomly drawn from a strictly decreasing beta distribution on $[0, 1]$. The parameter then enters the ethical component, both multiplicatively and as an exponent. This way, patients and physicians who are very opposed to being more corrupt than what is socially acceptable, will both have a more concave and larger ethics function than those who are not so opposed to engaging in activities more corrupt than what is socially acceptable. Physicians know the distribution of patient corruptibility and assume in every meeting that the patient as averagely corrupt. Patients do not have to estimate physicians' corruptibility in the model.

Finally, physicians' effort is private information and thus unobservable for the patients. Instead, patients estimate the effort exerted by their physician and calculate their expected utility based on that. Since the game simulated here is a iterated two-stage game where a new physician-patient pair meets in every step of the game, all patients expect their physician to exert "intermediate" effort

on its parameters, it can be either strictly decreasing or increasing, uniform or u-shaped. A unimodal distribution has a single max-value on the interior of the set it is defined on.

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which corresponds to the value 0.5 (i.e. patients do not know the distribution of physician effort and thus make a wild guess at 0.5), while physicians in fact can exert effort that corresponds to any value on the interval $[0, 1]^2$. It will be assumed in the simulations to come that physicians are rather willing to exert effort since they get only mild disutility from doing so.

This approach to modeling effort as private information is a rather unconventional one. A more standard approach to modeling would be to assume that patients did have a consistent belief about the effort exerted by physicians and, perhaps, that they could draw some inferences about the effort the physician is planning to exert from the contract offered (a signaling game). However, due to the complexity of the model and the numerical approach used, it is convenient to assume that patients are completely ignorant about the distribution of physicians when it comes to exerting effort both before and after physicians offer their contract. This assumption only affects the occurrence of contract failure in the game, and not the physicians' optimal contract. This is so since patients' expectation of effort only enters in the patient's evaluation of the contract. Consequently, when the group of treated patients is studied, the results are independent of the discussed assumption.

Even though there is no concrete information transmitted between stages of the game, it is assumed that physicians are forward looking. It is also assumed that after the treatment, patients can observe the health benefits they got from the treatment (which they could not fully foresee before the treatment since physician effort and their health status were unknown to them), and thus evaluate their post-treatment utility. Physicians assume that if, after a treatment, a patient finds out that he got utility less than his reservation utility from undergoing the treatment, the patient will spread a bad reputation about the physician which leads to fewer patients in the future.³ Therefore, physicians will constrain

²In a repeated game where information is transmitted between stages of the game, it would be possible to let expected effort depend on previously observed treatment outcomes for a given physician. If there is competition and a limited amount of patients, the frequency of patient arrival for each physician can be made dependent on the expected effort. A model in this spirit is discussed in McGuire (2000).

³Even if there is monopoly in the health sector, as is assumed here, physicians have to match patients' reservation utility from not undergoing treatment in order to attract patients.

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their utility maximization so that post-treatment utility they expect patients to get is larger than the utility physicians expect the patients would get from not undergoing the treatment.

Physicians have compassion for their patients that is expressed by including the treated patient's health function in the physicians' utility. The health function enters with a multiplicative constant in front of it that describes the level of compassion of the physician in question. This parameter is randomly drawn from a unimodal beta distribution on $[0, 1]$.

Finally, physicians are assumed to obtain fixed payments per patient from their employer (the state). These are always the same independent of the characteristics of the physician-patient meeting. This is a simplification that keeps a large part of the mechanisms of health care sectors outside of the model. Since the focus of the model is on the interaction of social norms and IPHCs, assuming a (nonrealistic) simple payment scheme for physicians is justified.

The patient and physician utility functions are inspired by Vaithianathan (2003). The main deviations from Vaithianathan's model are: (i) Instead of only giving the signs of the first and second derivatives, the functional form will be specified in order to use it for simulation. (ii) Treatment intensity will be made dependent on IPHC, not vice versa as in Vaithianathan (2003). (iii) The variables in patients' and physicians' utility functions are all defined on the interval $[0, 1]$. This way, the different units (health, money and effort) become comparable. (iv) The utility functions in Vaithianathan (2003) are extended to include physician effort and an ethical-social norm component for both patients and physicians.

The patients' utility from health care is defined as:

$$\begin{aligned} U_{pat}(z, e) &= H(\theta, t(z), e) + W(A, z) - M(z) \\ &= \left(\theta^\delta t(z)^\epsilon e^\zeta\right)^\alpha + \frac{|A-z|}{A-z} (|A-z|)^\beta - (1-r)(z - z_{norm})^r \end{aligned} \quad (3.1)$$

Where $H(\cdot)$ is the patient's health, $W(\cdot)$ is the patient's wealth and $M(\cdot)$ is the patient's ethical component. All three functions are increasing and concave in all their arguments. This implies that α, β and $r \in [0, 1]$. The same holds for $H(\cdot)$, $\delta, \epsilon, \zeta \in [0, 1]$, as well as $\delta + \epsilon + \zeta < 1$ since health benefits from treatment are assumed to have decreasing returns to scale. θ is the patient's initial health status, z is the amount of IPHC exchanged, e is the physician's

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effort and r is the patient's corruptibility. A corrupt patient has a high value of r and thus a small multiplicative parameter and a large exponent leading to a weakly concave, slowly increasing function $M(z)$ while a principled patient has a large multiplicative parameter and a small exponential which results in a strongly concave, rapidly increasing function $M(z)$. The variables θ, z, r and e are all defined on the interval $[0, 1]$. The treatment intensity (or quality) is given by $t(z) = \sqrt{(1 - t_{norm}^2)(z - z_{norm}) + t_{norm}^2}$. The functional form of $t(z)$ ensures that when $z = z_{norm}$, the treatment intensity equals t_{norm} which is exogenously given and depends on the quality of the health sector in the society studied. When patients do not have the possibility to borrow money for IPHCs that exceed their wealth, z is constrained to be less than or equal to A , so that $W(A, z) = \frac{|A-z|}{A-z} (|A-z|)^\beta$ in the patients' utility function is always larger or equal to zero. When patients have the possibility to borrow money, z can exceed A , resulting in $W(A, z) = \frac{|A-z|}{A-z} (|A-z|)^\beta < 0$, i.e. disutility from debt.

The physicians' utility function is defined as:

$$\begin{aligned} U_{phys}(z, e) &= \tilde{H}(\theta, t(z), e) + V(z) - M(z) - F(e) \\ &= q(\theta^\delta t(z)^\epsilon e^\zeta)^\alpha + (y + z)^\mu - w(1 - g)(z - z_{norm})^g - ke^\eta \end{aligned} \quad (3.2)$$

Where $\tilde{H}(\cdot) = qH(\cdot)$ is the physician's compassion towards the patient where q measures the level of compassion, $V(\cdot)$ is physician's monetary reward from giving treatment, $M(\cdot)$ is the physician's ethical component and $F(\cdot)$ describes the physician's sensitivity to effort. $\tilde{H}(\cdot), V(\cdot), M(\cdot)$ and $F(\cdot)$ are all strictly increasing and concave in all arguments. As a consequence, μ, g, α and $\eta \in [0, 1]$. y is the salary the physician obtains for treating a patient. It is assumed that y is fix, i.e. independent of effort and treatment intensity and the same for all physician-patient encounters. g and k describe the physician's corruptibility and his disutility from exerting effort. Finally, w is a parameter that calibrates the model so that a sufficiently large share of physicians demand the socially accepted amount of IPHC in their meetings with patients. In the next section where a simulation of the game is studied, $\alpha, \beta, \gamma, \delta, \epsilon, \zeta, \mu, \sigma, \eta, y$ and k will be given fix values for all patients and physicians while r, q, g, A, θ and g will vary between patients and physicians.

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The physician offers the patient a treatment contract given the results of his maximization, t^* and z^* . Due to the fact that the physician can only guess the patient's post-treatment utility from this contract (since wealth and corruptibility are private information) and since patients' pre-treatment utility can differ from their post-treatment utility (since information about health results is revealed post treatment), some patients will accept the contract offered and some patients will not. When a patient turns down a contract, no treatment takes place and the patient's utility equals his reservation utility. Now, the physician's utility maximization in each version of the game will be described.

3.2 The benchline case where IPHCs are non-existing

In the benchline case, IPHCs are not allowed. A consequence is that the ethical component in both the patients' and the physicians' utility functions is eliminated. The optimization faced by physicians thus is:

$$\begin{aligned}
 \max_e \quad & U_{phys}(e) = q\left(\theta^\delta t_{norm}^\epsilon e^\zeta\right)^\alpha + y^\mu - ke^\eta \\
 \text{s.t.} \quad & E_{phys}(U_{pat}(e)) \geq E_{phys}(\tilde{U}_{pat}) \\
 & e \in [0, 1]
 \end{aligned} \tag{3.3}$$

where $E_{phys}(U_{pat}(e))$ is the by the physician expected patient utility from a given treatment (where the physician guesses the patient's wealth and corruptibility as discussed above) and \tilde{U}_{pat} is the patient's reservation utility, i.e. the utility he would get from not getting the treatment. $t_{norm} = t(0)$ is exogenously given and depends on the quality of the health sector in the society.

In the benchline case, since IPHCs are excluded, the physician maximizes his utility over only one variable, effort = e . The problem is not convex for all values of q and k , hence, a heuristic algorithm⁴ is used for solving the optimization problem in the following chapter.

⁴A heuristic algorithm is an algorithm that uses domain specific information when searching for a solution. It is guaranteed that a heuristic algorithm finds a good solution, but it is not guaranteed that it finds the exact analytical solution to the problem (e.g. due to discrete step size when searching for an optimal solution).

3. THE MODEL

3.3 The social norm is IPHC = 0

Here, the social norm is not to pay any IPHCs. Still, patients and physicians have the possibility to go against the social norm and exchange an IPHC greater than zero. The optimization problem faced by physicians in this version of the model thus is:

$$\begin{aligned}
 \max_{e,z} \quad & U_{phys}(e, z) = q(\theta^\delta t(z)^\epsilon e^\zeta)^\alpha + (y + z)^\mu - w(1 - g)z^g - ke^n \\
 \text{s.t.} \quad & E_{phys}(U_{pat}(e, z)) \geq E_{phys}(\tilde{U}_{pat}) \\
 & e \in [0, 1] \\
 & \left(z \in [0, E_{phys}(A)] \right)
 \end{aligned} \tag{3.4}$$

Where, again, $E_{phys}(U_{pat}(e, z))$ is the utility the physician expects the patient to have from the treatment and \tilde{U}_{pat} is the patient's reservation utility. Since $z_{norm} = 0$, $t(z) = \sqrt{(1 - t_{norm}^2)z + t_{norm}^2}$ where t_{norm} is exogenously given. The model will be studied with and without the constraint presented inside parenthesis, i.e. with and without the possibility of borrowing money.

Due to the fact that the variable z (IPHC) is now included, the optimization problem faced by the physician is now over two variables, e and z . It can be shown that, as in the benchline case, the optimization problem is not convex.⁵ Thus, again, the solution to the problem will be found using a heuristic algorithm for non-convex problems.

3.4 The social norm is IPHC > 0

Here, the social norm is to pay a nonzero IPHC, referred to as z_{norm} in the model. Physicians and patients can follow the norm, or exchange an IPHC greater than the socially accepted amount, z_{norm} . The optimization problem faced by

⁵The Hessian matrices of the objective function and the constraints rewritten on standard form are not positive definite.

3. THE MODEL

physicians in this version of the model thus is:

$$\begin{aligned}
 \max_{e,z} \quad & U_{phys}(e, z) = q(\theta^\delta t(z)^\epsilon e^\zeta)^\alpha + (y + z)^\mu - w(1 - g)(z - z_{norm})^g - ke^\eta \\
 \text{s.t.} \quad & E_{phys}(U_{pat}(e, z)) \geq E_{phys}(\tilde{U}_{pat}) \\
 & e \in [0, 1] \\
 & \left(z \in [z_{norm}, E_{phys}(A)] \right)
 \end{aligned} \tag{3.5}$$

with the same variable definitions as in the previous section, except that now $t(z) = \sqrt{(1 - t_{norm}^2)(z - z_{norm}) + t_{norm}^2}$. Again, the model will be studied with and without the last constraint, and again it holds that the optimization problem is non-convex which implies that analytical methods do not work and a heuristic algorithm is needed to solve the problem.

3.5 Patient welfare

The patient welfare of the game will be calculated for all versions of the model using two types of welfare functions; a utilitarian function and a Rawlsian one. Also, the utilitarian welfare for the top and bottom 10% will be calculated and the top-bottom ratio taken. This gives some indications about equity in the grand game. Finally, health outcomes from treatment (average, top and bottom 10% and top-bottom ratio) and the average physician effort are studied. In all these cases, a Monte Carlo method will be used to estimate all the studied measures of patient welfare and health outcomes in the grand game. Moreover, both the group of all patients and the group of patients who have undergone treatment will be studied. Below are definitions of the patient welfare functions used.

The utilitarian social welfare function does not take the spread of utilities into account, only the total sum. The utilitarian patient welfare is given by:

$$\sum_{i=1}^n U_i^{pat} \tag{3.6}$$

According to the Rawlsian social welfare function, also known as the maximin welfare function, welfare is maximized when the utility of the individual with the

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lowest utility of all is maximized. The Rawlsian patient welfare is defined as:

$$\max(\min(U_i^{pat}), \quad \forall i \in [1, n]) \quad (3.7)$$

4

Simulations and results

4.1 Four examples of physician-patient encounters

Before simulating the grand game, the results of four physician-patient encounters in the benchline case and the two cases where IPHCs are allowed are compared. In the first encounter, an average physician-patient pair, i.e. with health, wealth and corruptibility on the mean of the beta distributions that will be used in the simulations, meets. In the second encounter, a principled physician with low compassion meets a corrupt patient. In the third encounter, a principled physician with high compassion meets a principled patient, and finally a principled physician with high compassion and a corrupt patient will interact. The outcome of these three meetings in all versions of the model will then be studied. In all four cases, the patient is characterized with initial health status $\theta = 0.5$ (and thus $E_{pat}(\theta) = 0.5$) and wealth, $A = 0.5$ (and thus $E_{phys}(A) = 0.5$). Other parameters are assigned the value they will have throughout the simulations that

4. SIMULATIONS AND RESULTS

follow. These are:

Exponentials in health function	δ	$= 0.25$	
	ϵ	$= 0.25$	
	ζ	$= 0.25$	
Exponential for $H(\cdot)$	α	$= 0.7$	
Exponential for $W(\cdot)$	β	$= 0.5$	
Exponential for $V(\cdot)$	μ	$= 0.5$	
Exponential for effort, e	η	$= 0.5$	(4.1)
Exponential for corruptibility	g	$= 1/6$	
Constant for effort, e	k	$= 0.1$	
Constant for corruptibility (phys. only),	w	$= 2$	
Physicians' salary	y	$= 0.5$	
Normal level of treatment	t_{norm}	$= 0.5$	
When IPHC norm non-zero	z_{norm}	$= 0.15$	

In the first case, the patient is characterized with corruptibility parameter $r = 1/6$ and the physician with corruptibility parameter $g = 1/6$ and compassion parameter $q = 1/6$. In the second case, the patient has $r = 0.8$ and the physician has $g = 0.1, q = 0.1$. In the third case, the patient has $r = 0.8$ and the physician has $g = 0.1, q = 0.5$. In the fourth and the last case, the patient has $r = 0.8$ and the physician has $g = 0.8, q = 0.8$.

If the contract offered by the physician is such that the patient's expected utility from it is less than zero, the patient does not accept the contract and the utility of both parties becomes zero (i.e. patients' reservation utility is assumed to be zero and patients can borrow for IPHCs larger than their wealth).

Here, and in the simulations that follow, Matlab's `fmincon` function with the interior point algorithm is used to solve the physician's utility maximization problem. Since the problem is not convex, the interior-point algorithm can only find local minima. To avoid ending up in a local minimum that is not a global minimum, two starting points for the algorithm are tested and the minimum of those is taken as the global minimum on the feasible set.¹ The results of the optimization are presented in table 7.1 in the appendix.

¹ $-U_{phys}$ is always non-convex in IPHC. An investigation of $\frac{\delta(-U_{phys})}{\delta e}$ and $\frac{\delta^2(-U_{phys})}{\delta e^2}$ when $IPHC = 0$ shows that $-U_{phys}$ is convex in e , except for small values of q and e . When $-U_{phys}$ is not convex in e , it is strictly increasing. As a result, Even though $-U_{phys}$ is non-convex in IPHC, it suffices to try two starting points, one with a high values of IPHC and one with a low value of IPHC to be sure to end up in the global minimum in one of the minimizations. This is so since there is only a single minimum in effort for a fixed value of IPHC

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The main conclusions to be drawn from the results are that generally, patient utility drops when IPHC becomes a norm in society and when the norm increases, while there seems not to be as a clear pattern for physician utility. If, however, patients are sufficiently corrupt, they can get higher utility when the norm is to pay an IPHC greater than zero, as is the case in the third simulated game in table 7.1. Also, if the physician is corrupt and has little compassion for his principled patient, a contract failure will take place due to the expectation of the patient that his utility from the treatment offered will be less than zero.

There is no guarantee in the model that physicians cannot get disutility from giving treatment, as becomes clear in the third game in table 7.1 where the physician gets disutility from treating the patient. This feature of the model is justified if physicians are assumed to be obliged by their employer to offer every patient who comes to them a treatment. An alternative would be to make the maximal utility of a physician (U_{phys}^*) in a given physician-patient encounter the third source of contract failure, in which case both parties would get a zero utility when $U_{phys}^* < 0$.

The four two-stage games analyzed here are examples of how the games that constitute the set of two-stage games which define the grand game look like. However, in the two-stage games of the grand game, patients' wealth A and health status θ will vary since they are randomly drawn in each of the two-stage games. Also, it was assumed here that the patient always had zero reservation utility and always borrows money when the IPHC demanded exceeds his wealth, while in the grand game, the case when patients' reservation utility is larger than zero as well as the case where patients cannot borrow money will also be studied.

4.2 The grand game: An iterated two-stage game

A set of 50 two-stage games which define one grand game are simulated. This is repeated 50 times and the average result of the 50 grand games gives the final outcome on patient welfare, health and physician effort for the group of all patients and the group of treated patients only. The fix parameters of the simulation are given in the previous section. Patients' wealth and health are randomly drawn from a *beta*(2,2) distribution which is unimodal and symmetric on [0,1]

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around its mean, 0.5. Physicians' compassion for patients' health improvement from the given treatment is randomly drawn from a $beta(2, 10)$ distribution which is a skew, unimodal distribution on $[0, 1]$ with mean value $1/6$. Finally, both patients' and physicians' corruptibility is randomly drawn from a strictly decreasing $beta(1, 5)$ distribution with mean value $1/6$. As discussed in the previous section, for all the versions of the model (benchline, $IPHC_{norm} = 0$ and $IPHC_{norm} > 0$), the grand game will be simulated for two types of patients, with zero reservation utility and non-zero reservation utility with and without the possibility to borrow money for the IPHCs when they exceed the patient's wealth. The results from running all model versions are presented in tables 7.2 to 7.5.

The results show that in all four versions of the model, patient welfare decreases in all its measures when IPHCs are introduced to the model and when $IPHC_{norm}$ increases, both for the group of all patients and for the group of treated patients only. The cause of this is twofold, an increased cost for the patients when they have to pay an IPHC and an increased probability of contract failure. Worse health outcomes from treatment do however not explain the decline in patient welfare when IPHCs enter the model and when $IPHC_{norm}$ increases. The results show that when all patients are taken into account, patients are not better off in the benchline case than in the other two cases when it comes to measures of health outcome. Even if equality measures of health are better in the benchline case when all patients are taken into account than in the other two cases,² average health of all patients is worse in the benchline case than in the other two cases.

When the case with $IPHC_{norm} = 0$ is compared to the case with $IPHC_{norm} > 0$, it turns out that when the group of all patients is studied, there is no obvious answer to which case has better health outcomes. When patients have zero reservation utility, the average health outcome is better in the $IPHC_{norm} > 0$ case than when $IPHC_{norm} = 0$ and vice versa when patients have non-zero reservation utility. This indicates that at least when patients have zero reservation utility, health outcomes do not explain the fall in utility when $IPHC_{norm}$ increases.

²This is due to the fact that in the benchline case, all patients undergo treatment. The functional form of patients' utility is such that even when physicians choose to exert no effort, the utility patients get from the treatment equals their reservation utility when it is non-zero (and exceeds it when it is zero).

4. SIMULATIONS AND RESULTS

If only the group of treated patients is taken into account, the result that utility decreases when IPHCs enter the model and $IPHC_{norm}$ increases sustains. The results on health outcomes differ however from the results when all patients are taken into account. Health outcomes of treated patients only is, in all cases and all measures, increasing when IPHCs are introduced and $IPHC_{norm}$ increases. The difference in health results between the group of all patients and the group of treated patients can be explained by the increased rate of contract failure when $IPHC_{norm}$ increases.

In order to explain the increase in health outcomes of treated patients when $IPHC_{norm}$ grows larger, one needs to study the patients' health function. From $H(\cdot)$ it can be seen that IPHCs are not the direct cause of better health outcomes since, as seen on the functional form of the health function, the normal treatment intensity/quality is the same ($= 0.5$) whether $IPHC_{norm} = 0$ or $IPHC_{norm} > 0$. It is only the deviation from the social norm that results in higher intensity and/or better quality treatment. Rather, the results show that it is increased physician effort that explains the increase in health outcomes. In all four versions of the model presented in tables 7.2 to 7.5, physicians mean effort exerted both for the group of treated patients and the group of all patients, including those who are not treated where no effort was exerted, is higher when $IPHC_{norm} > 0$ than when $IPHC_{norm} = 0$.

The big question then is why physicians choose to exert more effort when $IPHC_{norm} > 0$ than when $IPHC_{norm} = 0$. The answer lies in the fact that when $IPHC_{norm}$ increases, the probability that the constraint that ensures that the utility physicians expect patients to get from treatment exceeds the reservation utility physicians expect patients to have, binds more often which leads to higher optimal levels of effort for physicians. This becomes clearer when visualizing the utility of the average physician as well as the utility of another physician with corruptibility, $g = 0.1$ and compassion level, $q = 0.9$ when meeting a patient with initial health status equal to 0.5 who pays an IPHC equal to 0.2 when the social norm is to pay a bribe equal to 0.15. This is illustrated in figures 4.1 and 4.2. Note that varying the IPHC away from 0.2 will not change the shape of the physicians' utility functions, only the position of the maximum point in figure 4.1 and the values on the y-axis (utility).

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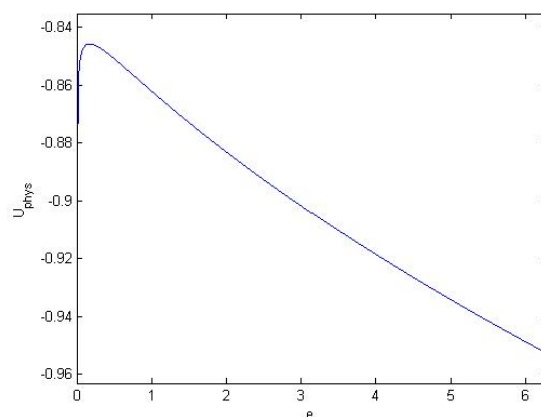


Figure 4.1: Utility function of the average physician when treating a patient with initial health status, $\theta = 0.5$ when IPHC is held fixed at 0.2 and $IPHC_{norm} = 0.15$

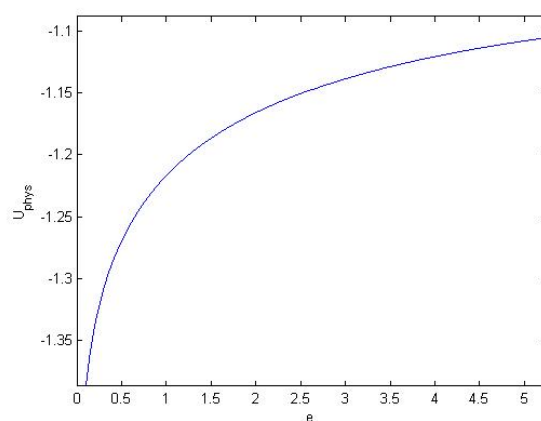


Figure 4.2: Utility function of a physician with $g = 0.1$ and $q = 0.95$ when treating a patient with initial health status, $\theta = 0.5$ when IPHC is held fixed at 0.2 and $IPHC_{norm} = 0.15$

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The figures show that the solution to the unconstrained optimization problem is $\text{effort} \approx 0$ in the former case and $\text{effort} = 1$ in the latter. Due to the fact that $\text{effort} \approx 0$ is likely to be outside the feasible area since expected patient utility has to exceed expected patient reservation utility, physicians will choose an effort level significantly larger than 0 when the patient-utility constraint binds. An increasing level of IPHC_{norm} leads to increased monetary disutility for patients from the IPHC demanded. Physicians therefore have to exert more effort in order to compensate for the disutility patients have from IPHCs to ensure that the patient utility equals the reservation utility the physician expects the patient to have. The result is higher effort when IPHC_{norm} increases.

5

Robustness

In order to study whether the results obtained in the previous chapter hold when assumptions and model details are changed, the simulations will be repeated for several alternative model setups. First, the multiplicative parameter in front of effort in the physicians' utility function will be modified, first upward to express increased disutility from effort and then downward to express decreased disutility from effort. Then, the distributional assumptions made about physician and patient characteristics will be altered. It will nonetheless still be assumed that the distribution for corruptibility is a strictly decreasing beta distribution on $[0, 1]$ and that the distribution for compassion is a unimodal beta distribution. Lastly, an alternative health function will be used. When altering the functional form of the health function, the exponentials in the function and the exponential for the function in the patients' utility function will be replaced.

Holding everything except the distributions the same as in the grand game in the previous section, the multiplicative parameter in front of effort disutility will be set to 10 and 0.01 respectively. Then, it will be assumed that physicians' corruptibility is $beta(1, 2)$ distributed, that patients' corruptibility is $beta(1, 20)$ distributed and that the level of physician compassion is $beta(2, 50)$ distributed (i.e. physicians are uncompassionate and corrupt while patients are principled). Finally, it will be assumed that the health function takes the new functional form $H(\theta, t(z), e) = (\theta^{0.4}t(z)^{0.3}e^{0.2})^{0.2}$ while everything else (including the beta distributions) is the same as in the grand game in the previous section.

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For all of the above described alternative versions of the model, the results, presented in tables 7.6 to 7.21 in the appendix, are similar to the results obtained in the previous chapter. Measures of patient welfare generally decrease when IPHCs are introduced and $IPHC_{norm}$ increases,¹ and the rate of contract failure increases when IPHCs are introduced and $IPHC_{norm}$ increases. However, contrary to the results in the previous section, health outcomes for treated patients in the benchline case are better than in the other two cases when the multiplicative parameter in front of effort is low, expressing low disutility from exerting effort for physicians. Despite this, when the multiplicative parameter in front of effort is low, the more interesting comparison between the two cases where IPHCs are taken into account shows results more similar to those in the previous section: There are better health outcomes when $IPHC_{norm} > 0$ than when $IPHC_{norm} = 0$ for the group of treated patients. This always holds when patients have non-zero reservation utility (i.e. mildly ill) in all of the model versions tried, but is less clear and does not hold in all versions of the model when patients have zero reservation utility. What explains this is the fact that when reservation utility is higher, the constraint describing physicians' forward looking behavior binds more often, leading to higher physician effort and thus better health outcomes for treated patients. Whether physicians' utility maximization is sensitive to this constraint depends on the functional form of their utility function and assumptions of the model, which is precisely what was altered in the alternative versions of the model studied here.

The results of the simulations when the alternative distributions of characteristics are used show a very high rate of contract failures that cannot be calibrated away by adjusting the calibration parameter, w . This is due to the fact the distribution of patients' corruptibility has a larger standard deviation than

¹There are a few exceptions, Rawlsian utility and the utilitarian utility of the bottom 10% are higher when $IPHC_{norm}=0$ when the multiplicative parameter in front of effort is large ($= 10$), patients have zero reservation utility and cannot borrow money for IPHCs. Also, equality measures of patient welfare such as Rawlsian welfare, the utilitarian welfare of the bottom 10% and the ratio of the top and bottom 10% turn out slightly better when $IPHC_{norm} = 0$ than when $IPHC_{norm} > 0$ in some of the versions of the model where alternative characteristics distributions are used. When this is the case, most often, the difference between the two measures is not significant at the 0.05 level.

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the distribution used in the previous section, hence physicians (who always assume that patients' corruptibility equals the mean of the distribution) more often over- or underestimate patients' corruptibility which results in an offered contract that does not fulfill the patients' expectations, i.e. does not match the patients' reservation utility.

6

Discussion

In this thesis, a Monte Carlo simulation was used to study the welfare effects of introducing informal payments for health care into a model of physician-patient interaction that takes social norms about informal payments into account. The main results are that traditional measures of patient welfare decrease when informal payments are introduced and when the socially accepted amount of informal payments for health care increases. Health outcomes, however, turn out to be better when it is the norm to pay an IPHC than when the socially accepted amount of IPHC is zero.

This holds for the group of all patients when patients have zero reservation utility, i.e. are severely ill and will almost certainly die from their illness, but also and even more strongly for the group of treated patients, irrespective of their reservation utility or ability to borrow money. However, robustness studies of the result for treated patients show that under certain circumstances, the result that health outcomes are better when $IPHC_{norm} > 0$ than when $IPHC_{norm} = 0$, only holds for treated patients with non-zero reservation utility. This is due to the fact that constraints that bind physicians to ensure that patients get at least their reservation utility from treatment bind more often than when patients' reservation utility is zero. The conclusion is that it is the patients' disutility from paying IPHC as well as increased probability of contract failure when IPHCs are introduced to the model and when $IPHC_{norm}$ increases that explains the drop in patient welfare observed in the results.

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At the same time, it is increased physician effort due to the more frequently binding of the constraint that describes physicians' forward looking nature that explains the increase in physician effort, which, in turn, explains better health outcomes when IPHCs are introduced and $IPHC_{norm}$ increases.

Lower social welfare in corrupt societies is a standard result in the literature (see e.g. Gupta et al. (2002)). The results of the model presented here that patient welfare goes down then IPHCs are introduced and increase is in line with this. Also, cross-country studies show that corruption and poor health outcomes go hand in hand (see e.g. Gupta et al. (2000)). The results of the simulation presented here show that although the overall effect of IPHCs might lead to negative health outcomes on the whole, as empirical evidence indicate, it is not the case that poor health outcomes are necessary when IPHCs are an established part of the health care sector. This thesis shows that when physicians are forward looking and physicians and patients do not bargain about IPHCs (i.e. contract failures occur), at least mildly ill patients (with non-zero reservation utility) who undergo treatment, get better health outcomes when paying IPHCs is a social norm than when it is not. This result is found by comparing the two more realistic versions of the model, a society where IPHCs can occur but where the social norm is not to pay an IPHC with a society where paying a certain level of IPHC is the social norm.¹

Despite better health outcomes when treated patients are studied, it is a fact that the number of patients who receive no treatment increases when $IPHC_{norm}$ goes up due to the increased probability of contract failure caused by asymmetric information about patients' initial health status, patients' wealth, physicians' level of compassion and patients' and physicians' corruptibility. Reducing the rate of contract failure when $IPHC_{norm} > 0$ would increase the health outcome of all patients and possibly lead to better overall health outcomes than in the $IPHC_{norm} = 0$ case.

Accordingly, a social planner in a society where $IPHC_{norm} > 0$ who wants to increase the average health outcome of all patients has the choice between reduc-

¹A society where IPHCs are non-existing like in the benchline case is probably very hard to find. It is therefore much more interesting to compare the two versions of the model where IPHCs in fact exist.

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ing $IPHC_{norm}$ and thus reducing the occurrence of contract failures while reducing the health outcome of treated patients, and only reducing the rate of contract failure by minimizing the effect of asymmetric information in the physician-patient meeting. Due to the fact that social norms are rigid and hard to alter, the former option is hard to realize. Minimizing asymmetric information is a more realistic way to go for the social planner.

Improved information about illnesses and symptoms accessible for patients would improve their estimation of their own health status and thus decrease the probability of contract failure. This could happen through information about symptoms and illnesses on the internet (given that patients have access to the internet) or through an independent telephone line (similar to “sjukvårdsupplysningen” in Sweden) where patients can get information about their symptoms and their gravity. In a very corrupt society, it could however be hard to maintain the independence of such a telephone line and thus assure the correctness of the information given there.

Another possibility would be to give physicians access to records about patients’ income and wealth. This is however an unrealistic option for policy makers since it is doubtful from a personal integrity point of view. Also, especially in less developed societies, it is not certain that such records exist.

Interesting extensions and variations of the model would for example be to “randomize” the model even more and thus make it more general. Making the disutility physicians get from exerting effort a randomly distributed part of their characteristic would be an interesting extension. Letting patients’ reservation utility randomly vary on the interval $[0, \sqrt{wealth}]$ would also make it possible to investigate a society where patient’s condition varies from mildly ill and non-life threatening to severe and life threatening. If this would be done, one would however need to make the reservation utility dependent on the initial health status, which is not necessary when only one group of patients, severely ill or mildly ill, is studied.

Also, it would be interesting to vary the salary physicians receive, as well as the normal treatment intensity or quality denoted t_{norm} in the model. Altering physicians salaries and t_{norm} could e.g. correspond to going from a less developed society (with lower t_{norm} and physician salary) to a more developed

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one (with higher t_{norm} and physician salary). Higher salary for physicians lowers their marginal utility of IPHCs and thus leads to contracts with lower demanded IPHC while higher t_{norm} improves health outcomes from treatment which leads to lower marginal utility from health outcomes for patients. The overall effect of these changes in the model is ambiguous since, while physicians will demand lower IPHCs, the higher treatment intensity/quality leads to lower marginal utility from improved health outcomes and thus less of an incentive to exert effort for physicians. If the physician salaries and the t_{norm} were set to small values corresponding to a poorly developed society, the results would be the opposite, physicians would demand higher IPHCs and higher marginal utility from health leads to more incentive to exert effort.

Another possibility would be to study the effects of IPHCs in a society where there is competition among physicians. Competition could be added to the model by increasing patients' reservation utility so that it matches the utility they would get if treated by an alternative physician. Also, by adding a time dimension to the model so that information is transmitted between stages of the game, the number of patient arriving to a certain physician depends on the reputation of the physician (which is worse when patients' utility from treatment is often lower than their reservation utility). This is in the spirit of the model presented in McGuire (2000).

Still another interesting extension would be to add an honest/dishonest dimension to physicians characteristics. Corrupt dishonest physicians would then demand IPHC larger than the norm but not increase the treatment quality or intensity as was expected by the patient paying the IPHC. In a game with time dimension and information transmitted between stages, this would have an additional effect on physician reputation and thus on the number of patients arriving to physicians.

Irrespective of all possible and interesting extensions of the model presented here, a next step in this line of research would be to simplify the model in order to solve it analytically and obtain more concrete results. The model studied here is to be seen as a numerical study of two corruption equilibria, $IPHC_{norm} = 0$ and $IPHC_{norm} = 0.15$, where patients' welfare and health outcomes are compared. The results are therefore both a good indication of which results to expect from

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analytically solving the (simplified) model and a good guide to what to focus on when modeling the physician-patient encounter analytically.

A first step in this direction would be to solve the model as a static Bayesian game. This would imply that patients' expectations about physician effort are endogenized so that patients have a consistent belief about to what extent physicians exert effort. In such a game, a Bayesian-Nash equilibrium that describes the game could be found and patient welfare calculated accordingly.

A second step would be to model the physician-patient encounter as a dynamic game with information transmitted between stages of the game (as in McGuire (2000), see footnote in chapter 3. p. 16) where a Perfect Bayesian Equilibrium describes the equilibrium of the game.

The results from solving the static Bayesian version of the model will hopefully be similar to the results obtained here. The occurrence of contract failure is however expected to differ from the model presented here since making patients' belief about physician effort consistent changes the utility patients' expect to get from a contract offered and thus the probability that they will accept the contract (See discussion in chapter 3.1).

When introducing dynamics to the model, the results will probably change more substantially. In a dynamic model where e.g. physicians are long-run players and patients are short-run players, the physicians will strive to hold up their good reputation and, given that they know the risk of contract failure, even when their "forward looking constraint" binds (due to asymmetric information), the physicians might choose an interior solution with lower utility than their optimal one in the one-shot game but where the risk of patient utility after treatment being lower than patient reservation utility is minimal.

7

Appendix

7.1 Tables

Model	e^*	z^*	U_{phys}	U_{pat}
$q = 1/6, r = g = 1/6$				
Benchline	0.0903	-	0.7629	1.2222
$z_{norm} = 0$	0.1006	0	0.7359	1.2186
$z_{norm} = 0.15$	0.0989	0.1500	0.8300	1.0990
$q = 0.1, r = 0.1, g = 0.9$				
Benchline	0.0188	-	0.7323	1.0983
$z_{norm} = 0$	0	0.5	0.	0
$z_{norm} = 0.15$	0	0.5	0	0
$q = 0.5, r = 0.8, g = 0.1$				
Benchline	1	-	0.9994	1.4917
$z_{norm} = 0$	0.6533	0.0343	-0.2674	1.4035
$z_{norm} = 0.15$	0.9194	0.15	0.9161	1.3647
$q = 0.8, r = 0.8, g = 0.8$				
Benchline	1	-	1.2348	1.4917
$z_{norm} = 0$	1	0.5	1.3503	0.7355
$z_{norm} = 0.2$	1	0.5	1.3956	0.7505

Table 7.1: Results from three different one-stage games

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	58.0740 (1.8218)	50.2113 (2.7682)	42.4739 (3.5865)
Rawlsian	0.6056 (0.1138)*	-0.1160 (0.1276)	-0.1586 (0.1249)
Bottom 10%Utilitarian	3.6911 (0.3401)	0.3672 (0.6104)	-0.1364 (0.3444)
Utilitarian $\frac{bottom}{top}$	0.3997 (0.0392)	0.0410 (0.0682)	-0.0156 (0.0393)
Utilitarian, treated	58.0740 (1.8218)	50.2113 (2.7682)	42.4739 (3.5865)
Rawlsian, treated	0.6056 (0.1138)	-0.0309 (0.2345)	-0.1354 (0.1626)
Bottom 10% Utilitarian, treated	0.0738 (0.0068)	0.0278 (0.0186)	0.0086 (0.0143)
Utilitarian $\frac{bottom}{top}$, treated	0.3997 (0.0392)	0.1776 (0.1190)	0.0540 (0.0904)
Mean health	0.3621(0.0275)	0.4410(0.0270)	0.4465 (0.0297)
Bottom 10% Health	0.0517 (0.0132)	0.0454 (0.0279)*	0.0277 (0.0306)
Health $\frac{bottom}{top}$	0.1251 (0.0327)*	0.1067 (0.0657)*	0.0656 (0.0726)*
Mean health, treated	0.0826 (0.0047)	0.0743 (0.0043)*	0.0761 (0.0048)
Bottom 10% Health, treated	0.0103 (0.0237)	0.0222 (0.0048)*	0.0237 (0.0050)
Health $\frac{bottom}{top}$, treated	0.1251 (0.0327)	0.2992 (0.0673)	0.3119 (0.0682)
Mean Phys. Effort	0.1817 (0.0364)	0.2915 (0.0471)	0.3117 (0.0471)
Mean Phys. Effort, treated	0.1817 (0.0364)	0.3064 (0.0486)	0.3372 (0.0486)
Contract failure, %	0%	4.84%	7.62%

Table 7.2: Results from the grand game when patients have zero reservation utility and can borrow money for IPHC. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	58.2420 (2.0346)	53.8229 (2.3798)	48.4697 (2.6090)
Rawlsian	0.6042 (0.0967)	0.3685 (0.1040)	0.2121 (0.1190)
Bottom 10% Utilitarian	3.6515 (0.3310)	2.6426 (0.3706)	1.8568 (0.4651)
Utilitarian $\frac{bottom}{top}$	0.3897 (0.0379)	0.2919 (0.0420)	0.2119 (0.0534)
Utilitarian, treated	58.2420 (2.0346)	48.1718 (3.6381)	41.0918 (3.6866)
Rawlsian, treated	0.6042 (0.0967)	0.4672 (0.1301)	0.2426 (0.1447)
Bottom 10% Utilitarian, treated	0.0730 (0.0066)	0.0626 (0.0113)	0.0432 (0.0130)
Utilitarian $\frac{bottom}{top}$, treated	0.3897 (0.0379)	0.3579 (0.0682)	0.2542 (0.0785)
Mean health	0.3637 (0.0259)	0.3949 (0.0321)	0.3826 (0.0320)
Bottom 10% Health	0.0511 (0.0106)*	0.0011 (0.0044)*	0 (0)
Health $\frac{bottom}{top}$	0.1237 (0.0270)*	0.0026 (0.0102)*	0 (-)
Mean health, treated	0.3637 (0.0259)	0.4701 (0.0268)	0.4861 (0.0251)
Bottom 10% Health, treated	0.0102 (0.0021)	0.0200 (0.0053)	0.0252 (0.0064)
Health $\frac{bottom}{top}$, treated	0.1237 (0.0270)	0.2421 (0.0656)	0.3088 (0.0835)
Mean Phys. Effort	0.1887 (0.0424)	0.2761 (0.0425)*	0.2677 (0.0419)
Mean Phys. Effort, treated	0.1887 (0.0424)	0.3286 (0.0470)*	0.3399 (0.0461)
Contract failure, %	0%	15.96%	21.28%

Table 7.3: Results from the grand game when patients have non-zero reservation utility and can borrow money for IPHC. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	57.6970 (1.7373)	49.8492 (3.2058)	41.9734 (3.5791)
Rawlsian	0.6186 (0.0950)*	-0.0725 (0.1120)*	-0.1113 (0.1229)*
Bottom 10% Utilitarian	3.6901 (0.3082)*	0.4787 (0.7183)*	-0.0972 (0.1896)
Utilitarian $\frac{bottom}{top}$	0.4018 (0.0367)*	0.0543 (0.0815)*	-0.0112 (0.0219)
Utilitarian, treated	57.6970 (1.7373)	49.8492 (3.2058)	41.9734 (3.5791)
Rawlsian, treated	0.6186 (0.0950)	-0.0002 (0.1880)	-0.0734 (0.1710)
Bottom 10% Utilitarian, treated	0.0738 (0.0062)	0.0299 (0.0157)	0.0164 (0.0132)*
Utilitarian $\frac{bottom}{top}$, treated	0.4018 (0.0367)*	0.1906 (0.1011)	0.0992 (0.0801)
Mean health	0.3537 (0.0248)	0.4568 (0.0214)	0.4844 (0.0237)
Bottom 10% Health	0.0486 (0.0120)*	0.0462 (0.0378)*	0.0065 (0.0152)*
Health $\frac{bottom}{top}$	0.1200 (0.0307)*	0.1100 (0.0899)*	0.0155 (0.0363)*
Mean health, treated	0.3537 (0.0248)	0.4568 (0.0214)	0.4844 (0.0237)
Bottom 10% Health, treated	0.0097 (0.0024)*	0.0223 (0.0039)	0.0256 (0.0051)*
Health $\frac{bottom}{top}$, treated	0.1200 (0.0307)*	0.2990 (0.0550)*	0.3196 (0.0678)*
Mean Phys. Effort	0.1716 (0.0371)	0.2813 (0.0397)	0.3012 (0.0383)
Mean Phys. Effort, treated	0.1716 (0.0371)	0.2968 (0.0410)	0.3461 (0.0426)
Contract failure, %	0%	5.2%	12.88%

Table 7.4: Results from the grand game when patients have zero reservation utility and cannot borrow money for IPHC. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	58.2529 (1.7789)	53.1770 (1.8002)	48.1711 (2.3281)
Rawlsian	0.6172 (0.1012)	0.3568 (0.1372)*	0.2442 (0.0615)*
Bottom 10% Utilitarian	3.7118 (0.3467)	2.5680 (0.5011)	1.8180 (0.3267)
Utilitarian $\frac{bottom}{top}$	0.3996 (0.0394)	0.2865 (0.0563)	0.2075 (0.0378)
Utilitarian, treated	58.2529 (1.7789)	47.6902 (3.0374)*	41.2589 (3.6096)
Rawlsian, treated	0.6172 (0.1012)	0.4376 (0.1691)*	0.4219 (0.1140)
Bottom 10% Utilitarian, treated	0.0742 (0.0069)	0.0607 (0.0124)	0.0587 (0.0114)
Utilitarian $\frac{bottom}{top}$, treated	0.3996 (0.0394)	0.3479 (0.0740)	0.3485 (0.0727)
Mean health	0.3654 (0.0285)*	0.3861 (0.0292)*	0.3626 (0.0340)*
Bottom 10% Health	0.0538 (0.0121)*	0.0023 (0.0164)*	0 (0)
Health $\frac{bottom}{top}$	0.1291 (0.0301)*	0.0055 (0.0388)*	0 (0)
Mean health, treated	0.3654 (0.0285)	0.4647 (0.0244)	0.4905 (0.0265)
Bottom 10% Health, treated	0.0108 (0.0024)	0.0205 (0.0053)	0.0259 (0.0065)
Health $\frac{bottom}{top}$, treated	0.1291 (0.0301)	0.2493 (0.0657)	0.3217 (0.0853)
Mean Phys. Effort	0.1893 (0.0393)*	0.2614 (0.0358)*	0.2590 (0.0378)*
Mean Phys. Effort, treated	0.1893 (0.0393)*	0.3148 (0.0409)	0.3506 (0.0455)*
Contract failure, %	0%	16.84%	26.08%

Table 7.5: Results from the grand game when patients have non-zero reservation utility and cannot borrow money for IPHC. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	36.4259 (1.3198)	25.0392 (2.9125)	17.5863 (2.6005)
Rawlsian	0.3082 (0.0641)*	-0.5129 (0.1496)*	-0.5605 (0.1116)*
Bottom 10%Utilitarian	2.0235 (0.2710)	-1.3220 (0.6900)	-1.8413 (0.5527)
Utilitarian $\frac{bottom}{top}$	0.3482 (0.0473)	-0.2374 (0.1242)	-0.3672 (0.1109)
Mean health, treated	0.0120 (0.0007)*	0.0167 (0.0017)*	0.0191 (0.0180)*
Bottom 10% Health, treated	0.0510 (0.0031)	0.0384 (0.0034)	0.0411 (0.0024)
Health $\frac{bottom}{top}$, treated	0.2156 (0.0253)	0.1553 (0.0594)*	0.1424 (0.0757)
Phys. Effort, treated	$1.8919 \cdot 10^{-7}$ $(4.9550 \cdot 10^{-8})^*$	$3.7321 \cdot 10^{-6}$ $(4.6269 \cdot 10^{-6})^*$	$1.3348 \cdot 10^{-5}$ $(9.5263 \cdot 10^{-6})^*$
Contract failure, %	0%	4.00%	7.76%

Table 7.6: Results from the grand game when patients have zero reservation utility and can borrow money for IPHC with multiplicative parameter for effort = -10 . Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	36.5980 (1.2423)	31.5929 (1.7099)	30.7597 (1.6255)
Rawlsian	0.2953 (0.0896)	-0.0295 (0.1509)*	-0.0011 (0.1116)
Bottom 10%Utilitarian	2.0204 (0.2694)	0.7673 (0.4635)*	0.8401 (0.4315)
Utilitarian $\frac{bottom}{top}$	0.3473 (0.0469)	0.1350 (0.0816)*	0.1557 (0.0801)
Mean health, treated	0.0118 (0.0007)	0.0195 (0.0017)*	0.0709 (0.0071)*
Bottom 10% Health, treated	0.0005 (0.00004)	0.0007 (0.0002)*	0.0028 (0.0005)*
Health $\frac{bottom}{top}$, treated	0.1894 (0.0212)	0.1532 (0.0588)*	0.1477 (0.0292)*
Phys. Effort, treated	$1.9497 \cdot 10^{-7}$ ($4.5712 \cdot 10^{-8}$)	$4.8937 \cdot 10^{-6}$ ($4.3149 \cdot 10^{-6}$)*	0.0013 (0.0032)*
Contract failure, %	0%	8.16%	12.40%

Table 7.7: Results from the grand game when patients have non-zero reservation utility and can borrow money for IPHC when the multiplicative parameter in front of effort = -10 . Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	36.2993 (1.5058)	25.2364 (2.4386)	18.2308 (2.5421)
Rawlsian	0.3136 (0.0713)*	-0.4564 (0.1562)*	-0.5082 (0.1334)*
Bottom 10%Utilitarian	2.0241 (0.2807)	-1.1265 (0.5870)	-1.4516 (0.5968)
Utilitarian $\frac{bottom}{top}$	0.3482 (0.0488)	-0.2026 (0.1059)	-0.2902 (0.1200)
Mean health, treated	0.0119 (0.0007)*	0.0164 (0.0017)*	0.0195 (0.0027)*
Bottom 10% Health, treated	0.0006 (0.00006)	0.0005 (0.0001)*	0.0008 (0.0002)*
Health $\frac{bottom}{top}$, treated	0.2164 (0.0283)*	0.1501 (0.0573)*	0.1355 (0.0615)*
Phys. Effort, treated	$1.8103 \cdot 10^{-7}$ ($5.3583 \cdot 10^{-8}$)*	$3.6073 \cdot 10^{-6}$ ($5.3420 \cdot 10^{-6}$)*	$1.4262 \cdot 10^{-5}$ ($1.0706 \cdot 10^{-5}$)*
Contract failure, %	0%	3.80%	12.76%

Table 7.8: Results from the grand game when patients have zero reservation utility and cannot borrow money for IPHC when the multiplicative parameter for effort = -10. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or t-test cannot be performed since the data is not approximately normal.

	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	36.4504 (1.1092)	31.2889 (1.7775)	30.7909 (1.4444)
Rawlsian	0.3099 (0.0589)	-0.0008 (0.1460)	0.1307 (0.0679)
Bottom 10%Utilitarian	2.0090 (0.2187)	0.8014 (0.4301)*	1.1945 (0.2105)
Utilitarian $\frac{bottom}{top}$	0.3470 (0.0383)	0.1423 (0.0765)*	0.2219 (0.0396)
Mean health, treated	0.0116 (0.0007)	0.0193 (0.0019)*	0.0663 (0.0077)*
Bottom 10% Health, treated	0.0005 (0.00005)	0.0007 (0.0002)*	0.0029 (0.0005)
Health $\frac{bottom}{top}$, treated	0.1942 (0.0252)	0.1516 (0.0620)	0.1536 (0.0321)*
Phys. Effort, treated	$1.7318 \cdot 10^{-7}$ ($4.5516 \cdot 10^{-8}$)*	$1.7318 \cdot 10^{-7}$ ($5.5492 \cdot 10^{-6}$)*	$8.4699 \cdot 10^{-4}$ ($4.0088 \cdot 10^{-4}$)*
Contract failure, %	0%	8.32%	16.36%

Table 7.9: Results from the grand game when patients have non-zero reservation utility and cannot borrow money for IPHC when the multiplicative parameter for effort = -10. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	72.7694 (1.4167)	54.5021 (3.0582)	47.3322 (3.1121)
Rawlsian	0.9901 (0.0910)*	0.0117 (0.0989)*	-0.0109 (0.0261)*
Bottom 10%Utilitarian	5.5188 (0.3126)*	0.7504 (0.7549)*	0.3101 (0.3729)*
Utilitarian $\frac{bottom}{top}$	0.5335 (0.0311)*	0.0787 (0.0792)*	0.0341 (0.0410)*
Mean health, treated	0.6924 (0.0121)	0.5922 (0.0195)	0.6061 (0.0180)
Bottom 10% Health, treated	0.0510 (0.0031)*	0.0384 (0.0034)	0.0411 (0.0042)*
Health $\frac{bottom}{top}$, treated	0.5267 (0.0325)*	0.4719 (0.0476)*	0.4918 (0.0575)*
Phys. Effort, treated	1.0000 (0.0003)*	0.6109 (0.0500)	0.6547 (0.0467) *
Contract failure, %	0%	5.88%	7.60%

Table 7.10: Results from the grand game when patients have zero reservation utility and can borrow money for IPHC when the multiplicative parameter for effort = -0.001 . Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	72.6837 (1.2377)	58.1691 (2.5180)	52.9662 (2.6277)
Rawlsian	0.9889 (0.0892)*	0.4417 (0.1165)	0.3257 (0.1138)*
Bottom 10%Utilitarian	5.5311 (0.2865)	2.9031 (0.3652)	2.3573 (0.5081)
Utilitarian $\frac{bottom}{top}$	0.5366 (0.0289)	0.3029 (0.0388)*	0.2585 (0.0561)*
Mean health, treated	0.6908 (0.0148)	0.6145 (0.0205)*	0.6185 (0.0203)
Bottom 10% Health, treated	0.0491 (0.0049)	0.0374 (0.0058)	0.0392 (0.0059)
Health $\frac{bottom}{top}$, treated	0.5058 (0.0503)	0.4205 (0.0721)	0.4399 (0.0756)
Phys. Effort, treated	0.9996 (0.0017)*	0.6919 (0.0458)*	0.6956 (0.0472)*
Contract failure, %	0%	19.00%	20.68%

Table 7.11: Results from the grand game when patients have non-zero reservation utility and cannot borrow money for IPHC when the multiplicative parameter for effort = -0.001 . Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	72.5620 (1.3494)	54.2528 (2.7690)	45.4683 (3.2305)
Rawlsian	0.9766 (0.0844)*	0.0156 (0.0581)*	-0.0009 (0.0063)*
Bottom 10%Utilitarian	5.4755 (0.2886)	0.8245 (0.7089)*	0.0261 (0.0894)*
Utilitarian $\frac{bottom}{top}$	0.5280 (0.0291)	0.0872 (0.0750)	0.0029 (0.0099)
Mean health, treated	0.6877 (0.0139)	0.5751 (0.0174)	0.5947 (0.0175)
Bottom 10% Health, treated	0.0496 (0.0039)	0.0372 (0.0039)	0.0447 (0.0051)
Health $\frac{bottom}{top}$, treated	0.5133 (0.0410)*	0.4592 (0.0559)	0.5068 (0.0655)
Phys. Effort, treated	0.9994 (0.0044)*	0.5664 (0.0407)	0.6152 (0.0330)*
Contract failure, %	0%	5.76%	14.56%

Table 7.12: Results from the grand game when patients have zero reservation utility and cannot borrow money for IPHC when the multiplicative parameter for effort = -0.001 . Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	72.8982 (1.2262)	58.0814 (1.9323)	52.7369 (2.0571)
Rawlsian	1.0058 (0.0837)	0.4202 (0.1189)	0.2776 (0.0908)
Bottom 10%Utilitarian	5.5710 (0.2595)	2.8597 (0.3969)	2.1118 (0.4822)
Utilitarian $\frac{bottom}{top}$	0.5379 (0.0263)	0.2968 (0.0420)	0.2295 (0.0527)
Mean health, treated	0.6885 (0.0134)	0.6104 (0.0185)	0.6156 (0.0201)
Bottom 10% Health, treated	0.0500 (0.0041)	0.0377 (0.0047)	0.0422 (0.0066)
Health $\frac{bottom}{top}$, treated	0.5170 (0.0427)*	0.4200 (0.0603)	0.4759 (0.0833)
Phys. Effort, treated	0.9992 (0.0034)*	0.6861 (0.0412)*	0.6931 (0.0507)
Contract failure, %	0%	19.52%	24.88%

Table 7.13: Results from the grand game when patients have non-zero reservation utility and cannot borrow money for IPHC when the multiplicative parameter for effort = -0.001 . Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	45.1768 (1.3193)	23.4189 (3.3430)	15.3552 (3.3245)
Rawlsian	0.4661 (0.0892)*	-0.4747 (0.0782)*	-0.4699 (0.0927)*
Bottom 10%Utilitarian	2.8233 (0.0406)	-1.6303 (0.5077)*	-1.6260 (0.4677)
Utilitarian $\frac{bottom}{top}$	0.3964 (0.0439)	-0.2169 (0.0685)	-0.2404 (0.0731)
Mean health, treated	0.1175 (0.0083)	0.3261 (0.0340)*	0.3189 (0.0320)
Bottom 10% Health, treated	0.0032 (0.0007)	0.0067 (0.0020)	0.0081 (0.0021)
Health $\frac{bottom}{top}$, treated	0.1098 (0.0272)*	0.0882 (0.0275)	0.1063 (0.0291)*
Phys. Effort, treated	0.0028 (0.0009)*	0.1727 (0.0455)*	0.1759 (0.0470)*
Contract failure, %	0%	19.68%	29.40%

Table 7.14: Results from the grand game when patients have zero reservation utility and can borrow money for IPHC with alternative beta distributions for physician and patient characteristics. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	45.0793 (1.2835)	37.9829 (2.1039)	36.3358 (1.8955)
Rawlsian	0.4496 (0.0878)	0.1032 (0.1454)	0.1695 (0.1086)
Bottom 10%Utilitarian	2.7998 (0.2881)	1.3073 (0.4117)	1.4494 (0.3159)
Utilitarian $\frac{bottom}{top}$	0.3926 (0.0426)	0.1731 (0.0553)	0.2077 (0.0478)
Mean health, treated	0.1165 (0.0100)*	0.3356 (0.0424)*	0.3665 (0.0517)
Bottom 10% Health, treated	0.0031 (0.0006)*	0.0054 (0.0024)*	0.0137 (0.0068)*
Health $\frac{bottom}{top}$, treated	0.1062 (0.0240)*	0.0688 (0.0324)*	0.1552 (0.0816)*
Phys. Effort, treated	0.0029 (0.0013)*	0.2060 (0.0602)	0.2375 (0.0702)*
Contract failure, %	0%	46.08%	58.28%

Table 7.15: Results from the grand game when patients have non-zero reservation utility and can borrow money for IPHC with alternative beta distributions for physician and patient characteristics. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	45.0605 (1.4044)	23.7358 (3.4855)	15.1723 (3.0355)
Rawlsian	0.4440 (0.0774)	-0.4780 (0.0673)*	-0.4976 (0.0813)
Bottom 10%Utilitarian	2.7325 (0.2251)	-1.7294 (0.4002)*	-1.8232 (0.4068)
Utilitarian $\frac{bottom}{top}$	0.3835 (0.0343)	-0.2301 (0.0548)	-0.2715 (0.0652)
Mean health, treated	0.1185 (0.0110)	0.3204 (0.0269)	0.3086 (0.0302)
Bottom 10% Health, treated	0.0031 (0.0006)*	0.0061 (0.0020)*	0.0072 (0.0020)*
Health $\frac{bottom}{top}$, treated	0.1017 (0.0250)	0.0812 (0.0283)	0.0932 (0.0283)
Phys. Effort, treated	0.0031 (0.0014)*	0.1604 (0.0323)	0.1639 (0.0416)*
Contract failure, %	0%	17.68%	30.52%

Table 7.16: Results from the grand game when patients have zero reservation utility and cannot borrow money for IPHC with alternative beta distributions for physician and patient characteristics. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	45.2966 (1.2349)	38.1228 (1.8650)	36.4899 (1.4703)
Rawlsian	0.4440 (0.0793)	0.0433 (0.1666)	0.2146 (0.0724)
Bottom 10%Utilitarian	2.8140 (0.2716)	1.3260 (0.4950)	1.5602 (0.2875)
Utilitarian $\frac{bottom}{top}$	0.3957 (0.0661)	0.2257 (0.0454)	0.0403 (0.3957)
Mean health, treated	0.1184 (0.0076)	0.3386 (0.0408)	0.3705 (0.0435)
Bottom 10% Health, treated	0.0034 (0.0006)	0.0054 (0.0020)	0.0124 (0.0067)
Health $\frac{bottom}{top}$, treated	0.1150 (0.0231)	0.0654 (0.0257)*	0.1391 (0.0789)
Phys. Effort, treated	0.0028 (0.0009)*	0.2126 (0.0463)*	0.2460 (0.0692)*
Contract failure, %	0%	47.72%	59.64%

Table 7.17: Results from the grand game when patients have non-zero reservation utility and cannot borrow money for IPHC with alternative beta distributions for physician and patient characteristics. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	70.8511 (52.8419)*	61.6390 (3.4303)*	52.8419 (3.4148)*
Rawlsian	0.9633 (0.0805)*	0.01860 (0.1405)*	-0.0443 (0.0678)*
Bottom 10%Utilitarian	5.3664 (0.2771)	1.2797 (0.9868)	1.2797 (0.5159)
Utilitarian $\frac{bottom}{top}$	0.5342 (0.0291)*	0.1262 (0.0974)*	0.0380 (0.0527)*
Mean health, treated	0.2251 (0.0120)	0.3749 (0.0207)	0.3880 (0.0220)
Bottom 10% Health, treated	0.0093 (0.0016)*	0.0169 (0.0025)	0.0166 (0.0029)
Health $\frac{bottom}{top}$, treated	0.2062 (0.0376)*	0.2577 (0.0468)	0.2517 (0.0484)
Phys. Effort, treated	0.0150 (0.0027)	0.1943 (0.0357)	0.2212 (0.0331)
Contract failure, %	0%	2.96%	5.20%

Table 7.18: Results from the grand game when patients have zero reservation utility and can borrow money for IPHC with an alternative health function. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	71.2032 (1.1384)	64.0091 (2.5685)	57.4867 (2.3434)
Rawlsian	0.9729 (0.0839)	0.4364 (0.1341)	0.3458 (0.1141)
Bottom 10%Utilitarian	5.4027 (0.2446)	3.0677 (0.4867)	2.5503 (0.3590)
Utilitarian $\frac{bottom}{top}$	0.5364 (0.0258)	0.3015 (0.0481)	0.2608 (0.0371)
Mean health, treated	0.2276 (0.0108)	0.3832 (0.0245)	0.4120 (0.0232)
Bottom 10% Health, treated	0.0101 (0.0015)	0.0176 (0.0034)	0.0221 (0.0040)
Health $\frac{bottom}{top}$, treated	0.2232 (0.0352)	0.2527 (0.0352)	0.3037 (0.0608)
Phys. Effort, treated	0.0157 (0.0026)	0.2064 (0.0394)	0.2546 (0.0342)
Contract failure, %	0%	10.08%	16.64%

Table 7.19: Results from the grand game when patients have non-zero reservation utility and can borrow money for IPHC with an alternative health function. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or, a t-test cannot be performed since the data is not approximately normal.

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	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	71.2759 (1.5739)	62.0941 (3.1447)	52.1762 (4.1320)
Rawlsian	1.0032 (0.0890)*	0.0230 (0.0932)*	-0.0082 (0.0234)
Bottom 10%Utilitarian	5.4950 (0.3349)	1.3604 (0.8935)	0.1327 (0.2724)
Utilitarian $\frac{bottom}{top}$	0.5458 (0.0347)	0.1344 (0.0883)	0.0136 (0.0279)
Mean health, treated	0.2290 (0.0111)*	0.3775 (0.0161)*	0.4034 (0.0242)
Bottom 10% Health, treated	0.0097 (0.0014)	0.0173 (0.0030)*	0.0198 (0.0041)*
Health $\frac{bottom}{top}$, treated	0.2150 (0.0341)*	0.2666 (0.0521)*	0.2840 (0.0614)*
Phys. Effort, treated	0.0152 (0.0031)*	0.1931 (0.0329)*	0.2404 (0.0453)*
Contract failure, %	0%	3.20%	11.44%

Table 7.20: Results from the grand game when patients have zero reservation utility and cannot borrow money for IPHC with an alternative health function. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

	Benchline	$z_{norm} = 0$	$z_{norm} = 0.15$
Utilitarian	71.0217 (1.1961)	64.1738 (2.5368)	56.7839 (2.7767)
Rawlsian	0.9841 (0.0946)	0.4532 (0.1164)*	0.2792 (0.0903)*
Bottom 10%Utilitarian	5.3971 (0.2716)*	3.0981 (0.4950)*	2.1098 (0.2875)
Utilitarian $\frac{bottom}{top}$	0.3957 (0.2968)*	0.2257 (0.5100)*	0.0403 (0.5395)
Mean health, treated	0.2281 (0.0116)*	0.3889 (0.0194)	0.4205 (0.0233)*
Bottom 10% Health, treated	0.0098 (0.0015)	0.0172 (0.0030)	0.0244 (0.0050)
Health $\frac{bottom}{top}$, treated	0.2209 (0.0372)	0.2434 (0.0476)	0.3390 (0.0759)
Phys. Effort, treated	0.0150 (0.0031)*	0.2170 (0.0394)	0.2636 (0.0366)*
Contract failure, %	0%	9.72%	21.12%

Table 7.21: Results from the grand game when patients have non-zero reservation utility and cannot borrow money for IPHC with with an alternative health function. Sample standard deviation in parentheses. *: Either the null hypotheses that the value in the box differs from the value to its right (benchline being to the right of $z_{norm} = 0.15$) cannot be rejected at the 0.05 significance level according to a t-test, or a t-test cannot be performed since the data is not approximately normal.

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7.2 Programming codes

```
\begin{verbatim}
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% GRAND MAIN.
% This is the main program that performs the Monte Carlo estimations of
% social welfare, health and phys. effort.
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clear all
tic
global h tnorm y r g a q htilde atilde znorm constr resutility borrow h1 h2 r1 r2 g1 g2 a1 a2
    q1 q2 w
constr=1;          %sets model version
resutility=0;
borrow=0;
n=50;             %numer of iterations
k=50;

w=4; %Calibration parameter
%Distribution parameters
h1=2;
h2=2;
r1=1;
r2=5;
g1=1;
g2=5;
a1=2;
a2=2;
q1=2;
q2=10;

countfailureU1=zeros(n,1);
countfailureZ1=zeros(n,1);
countfailureU2=zeros(n,1);
countfailureZ2=zeros(n,1);
countfailureU3=zeros(n,1);
countfailureZ3=zeros(n,1);
countfailureUZ2=zeros(n,1);
countfailureUZ3=zeros(n,1);

SoWelUtilitarianBenchline=zeros(n,1);
SoWelUtilitarianIPHCzero=zeros(n,1);
SoWelUtilitarianIPHCzeroTwo=zeros(n,1);

SoWelUtilitarianBenchlineTreated=zeros(n,1);
SoWelUtilitarianIPHCzeroTreated=zeros(n,1);
SoWelUtilitarianIPHCzeroTwoTreated=zeros(n,1);

SoWelRawlsianBenchlineTreated=zeros(n,1);
SoWelRawlsianIPHCzeroTreated=zeros(n,1);
SoWelRawlsianIPHCzeroTwoTreated=zeros(n,1);
SoWelBNBenchlineTreated=zeros(n,1);
SoWelBNIPHCzeroTreated=zeros(n,1);
SoWelBNIPHCzeroTwoTreated=zeros(n,1);

SoWelRawlsianTREATEDBenchline=zeros(n,1);
SoWelRawlsianTREATEDIPHCzero=zeros(n,1);
SoWelRawlsianTREATEDIPHCzeroTwo=zeros(n,1);

SoWelRawlsianBenchline=zeros(n,1);
SoWelRawlsianIPHCzero=zeros(n,1);
SoWelRawlsianIPHCzeroTwo=zeros(n,1);
SoWelBNBenchline=zeros(n,1);
SoWelBNIPHCzero=zeros(n,1);
SoWelBNIPHCzeroTwo=zeros(n,1);
\end{verbatim}
```

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```
BottomUtilitarianBenchline=zeros(n,1);
BottomUtilitarianIPHCzero=zeros(n,1);
BottomUtilitarianIPHCzeroTwo=zeros(n,1);

BottomUtilitarianBenchlineTreated=zeros(n,1);
BottomUtilitarianIPHCzeroTreated=zeros(n,1);
BottomUtilitarianIPHCzeroTwoTreated=zeros(n,1);

TopUtilitarianBenchline=zeros(n,1);
TopUtilitarianIPHCzero=zeros(n,1);
TopUtilitarianIPHCzeroTwo=zeros(n,1);

TopUtilitarianBenchlineTreated=zeros(n,1);
TopUtilitarianIPHCzeroTreated=zeros(n,1);
TopUtilitarianIPHCzeroTwoTreated=zeros(n,1);

TreatedUtilitarianBenchline=zeros(n,1);
TreatedUtilitarianIPHCzero=zeros(n,1);
TreatedUtilitarianIPHCzeroTwo=zeros(n,1);

UtilitarianTrBottBenchline = zeros(n,1);
UtilitarianTrBottIPHCzero = zeros(n,1);
UtilitarianTrBottIPHCzeroTwo = zeros(n,1);

UtilitarianTrTopBenchline = zeros(n,1);
UtilitarianTrTopIPHCzero = zeros(n,1);
UtilitarianTrTopIPHCzeroTwo = zeros(n,1);

MeanEffortBenchline=zeros(n,1);
MeanEffortIPHCzero=zeros(n,1);
MeanEffortIPHCzeroTwo=zeros(n,1);

MeanEffortBenchlineAll=zeros(n,1);
MeanEffortIPHCzeroAll=zeros(n,1);
MeanEffortIPHCzeroTwoAll=zeros(n,1);

MeanHealthBenchline=zeros(n,1);
MeanHealthIPHCzero=zeros(n,1);
MeanHealthIPHCzeroTwo=zeros(n,1);

MeanHealthBenchlineAll=zeros(n,1);
MeanHealthIPHCzeroAll=zeros(n,1);
MeanHealthIPHCzeroTwoAll=zeros(n,1);

BottomHealthBenchline=zeros(n,1);
BottomHealthIPHCzero=zeros(n,1);
BottomHealthIPHCzeroTwo=zeros(n,1);

BottomHealthBenchlineAll=zeros(n,1);
BottomHealthIPHCzeroAll=zeros(n,1);
BottomHealthIPHCzeroTwoAll=zeros(n,1);

TopHealthBenchline=zeros(n,1);
TopHealthIPHCzero=zeros(n,1);
TopHealthIPHCzeroTwo=zeros(n,1);

TopHealthBenchlineAll=zeros(n,1);
TopHealthIPHCzeroAll=zeros(n,1);
TopHealthIPHCzeroTwoAll=zeros(n,1);

soWelBNBenchline=1;
soWelBNIPHCzero=1;
soWelBNIPHCzeroTwo=1;

sumz1=zeros(n,1);
sumz2=zeros(n,1);

%Monte Carlo estimation of social welfare/health
for j=1:n
```

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```
tnorm=0.5;
znorm=0.15;
y=0.5;
eBenchline=zeros(k,1);
UphysBenchline=zeros(k,1);
UpatBenchline=zeros(k,1);
UpatRealBenchline=zeros(k,1);
HealthBenchline=zeros(k,1);
UpatTreatedBenchline=zeros(k,1);

eIPHCzero=zeros(k,1);
zIPHCzero=zeros(k,1);
UphysIPHCzero=zeros(k,1);
UpatIPHCzero=zeros(k,1);
UpatRealIPHCzero=zeros(k,1);
HealthIPHCzero=zeros(k,1);
UpatTreatedIPHCzero=zeros(k,1);

eIPHCzeroTwo=zeros(k,1);
zIPHCzeroTwo=zeros(k,1);
UphysIPHCzeroTwo=zeros(k,1);
UpatIPHCzeroTwo=zeros(k,1);
UpatRealIPHCzeroTwo=zeros(k,1);
HealthIPHCzeroTwo=zeros(k,1);
UpatTreatedIPHCzeroTwo=zeros(k,1);

zas1=zeros(k,1);
zas2=zeros(k,1);

countU1=zeros(k,1);
countZ1=zeros(k,1);
countU2=zeros(k,1);
countZ2=zeros(k,1);
countU3=zeros(k,1);
countZ3=zeros(k,1);
countUZ2=zeros(k,1);
countUZ3=zeros(k,1);

% i grand games
for i=1:k
    %Random draw of characteristics
    h = betarnd(h1,h2); %symmetric beta, mean=0.5
    r = betarnd(r1,r2); %asymmetric beta, mean=1/6
    g = betarnd(r1,r2);
    a = betarnd(a1,a2);
    q = betarnd(q1,q2);

    %sets E(characteristics)
    if a <=1/3
        atilde=1/6;
    else if a <=2/3
        atilde = 0.5;
    else if a > 2/3
        atilde = 0.8333;
    end
    end
end

if h <=1/3
    htilde=1/6;
else if h <=2/3
    htilde = 0.5;
else if h > 2/3
    htilde = 0.8333;
end
end
end

%This runs if reservation utility is zero
if resutility==0
```

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```
[ebenchline, Uphysbenchline, Upatbenchline, UpatRealbenchline, Healthbenchline]=
    benchline();
QBenchline=UpatRealbenchline
if Upatbenchline < 0
    'exceed'
    ebenchline=0;
    Uphysbenchline=0;
    Upatbenchline=0;
    UpatRealbenchline=0;
    QBenchline=0;
    Healthbenchline=0;
    countU1(i)=1;
    a
end

[xIPHCzero, uphysIPHCzero, upatIPHCzero, upatRealIPHCzero, healthIPHCzero]=
    IPHCzero();
QIPHCzero=upatRealIPHCzero
if upatIPHCzero < 0
    'exceed'
    xIPHCzero(1)=0;
    uphysIPHCzero=0;
    upatIPHCzero=0;
    upatRealIPHCzero=0;
    healthIPHCzero=0;
    QIPHCzero=0;
    countU2(i)=1;
    countUZ2(i)=1;
    a
end

%This runs if patients cannot borrow
if borrow==0
    if xIPHCzero(2) > a
        'exceeded'
        xIPHCzero(1)=0;
        uphysIPHCzero=0;
        upatIPHCzero=0;
        upatRealIPHCzero=0;
        healthIPHCzero=0;
        QIPHCzero=0;
        countZ2(i)=1;
        countUZ2(i)=1;
        a
    end
end

if xIPHCzero(2) < 0.00001 && xIPHCzero(2) > -0.00001
    zas1(i)=1;
end

[xIPHCzeroTwo, uphysIPHCzeroTwo, upatIPHCzeroTwo, upatRealIPHCzeroTwo,
    healthIPHCzeroTwo]=IPHCzerotwo();
QIPHCzeroTwo=upatRealIPHCzeroTwo
if upatIPHCzeroTwo < 0
    'exceed'
    xIPHCzeroTwo(1)=0;
    uphysIPHCzeroTwo=0;
    upatIPHCzeroTwo=0;
    upatRealIPHCzeroTwo=0;
    healthIPHCzeroTwo=0;
    QIPHCzeroTwo=0;
    countU3(i)=1;
    countUZ3(i)=1;
    a
end
if borrow == 0
    if xIPHCzeroTwo(2) > a
```


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```

        'exceeded'
        xIPHCzeroTwo(1)=0;
        uphysIPHCzeroTwo=0;
        upatIPHCzeroTwo=0;
        upatRealIPHCzeroTwo=0;
        healthIPHCzeroTwo=0;
        QIPHCzeroTwo=0;
        countZ3(i)=1;
        countUZ3(i)=1;
    end
end
if xIPHCzeroTwo(2)<znorm+0.00001 && xIPHCzeroTwo(2)>znorm-0.00001
    zas2(i)=1;
end
end

%This runs if patients' reservation utility is non-zero
if resutility==1
    [ebenchline, Uphysbenchline, Upatbenchline, UpatRealbenchline, Healthbenchline]=
        benchline();
    QBenchline=UpatRealbenchline;
    if Upatbenchline < a^0.5
        'exceed'
        ebenchline=0;
        Uphysbenchline=0;
        Upatbenchline=a^0.5;
        UpatRealbenchline=a^0.5;
        Healthbenchline=0;
        QBenchline=0;
        countU1(i)=1;
        a
    end

    [xIPHCzero, uphysIPHCzero, upatIPHCzero, upatRealIPHCzero, healthIPHCzero]=
        IPHCzero();
    QIPHCzero=upatRealIPHCzero;
    if upatIPHCzero < a^0.5
        'exceed'
        xIPHCzero(1)=0;
        uphysIPHCzero=0;
        upatIPHCzero=a^0.5;
        upatRealIPHCzero=a^0.5;
        healthIPHCzero=0;
        QIPHCzero=0;
        countU2(i)=1;
        countUZ2(i)=1;
        a
    end
    if borrow == 0
        if xIPHCzero(2) > a
            'exceeded'
            xIPHCzero(1)=0;
            uphysIPHCzero=0;
            upatIPHCzero=a^0.5;
            upatRealIPHCzero=a^0.5;
            healthIPHCzero=0;
            QIPHCzero=0;
            countZ2(i)=1;
            countUZ2(i)=1;
            a
        end
    end
end
if xIPHCzero(2)<0.00001 && xIPHCzero(2)>-0.00001
    zas1(i)=1;
end

[xIPHCzeroTwo, uphysIPHCzeroTwo, upatIPHCzeroTwo, upatRealIPHCzeroTwo,
    healthIPHCzeroTwo]=IPHCzerotwo();

```

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```

QIPHCzeroTwo=upatRealIPHCzeroTwo;
if upatIPHCzeroTwo < a^0.5
    'exceeded'
    xIPHCzeroTwo(1)=0;
    uphysIPHCzeroTwo=0;
    upatIPHCzeroTwo=a^0.5;
    upatRealIPHCzeroTwo=a^0.5;
    healthIPHCzeroTwo=0;
    QIPHCzeroTwo=0;
    countU3(i)=1;
    countUZ3(i)=1;
    a
end
if borrow == 0
    if xIPHCzeroTwo(2) > a
        'exceeded'
        xIPHCzeroTwo(1)=0;
        uphysIPHCzeroTwo=0;
        upatIPHCzeroTwo=a^0.5;
        upatRealIPHCzeroTwo=a^0.5;
        healthIPHCzeroTwo=0;
        QIPHCzeroTwo=0;
        countZ3(i)=1;
        countUZ3(i)=1;
        a
    end
end
if xIPHCzeroTwo(2)<znorm+0.00001 && xIPHCzeroTwo(2)>znorm-0.00001
    zas2(i)=1;
end
end

%saves the results of each phys-pat. encounter in a vector
eBenchline(i,1)=ebenchline;
UphysBenchline(i,1)=Uphysbenchline*(-1);
UpatBenchline(i,1)=Upatbenchline;
UpatRealBenchline(i,1)=UpatRealbenchline;
HealthBenchline(i,1)=Healthbenchline;
UpatTreatedBenchline(i,1)=QBenchline;

eIPHCzero(i,1)=xIPHCzero(1);
zIPHCzero(i,1)=xIPHCzero(2);
UphysIPHCzero(i,1)=uphysIPHCzero*(-1);
UpatIPHCzero(i,1)=upatIPHCzero;
UpatRealIPHCzero(i,1)=upatRealIPHCzero;
HealthIPHCzero(i,1)=healthIPHCzero;
UpatTreatedIPHCzero(i,1)=QIPHCzero;

eIPHCzeroTwo(i,1)=xIPHCzeroTwo(1);
zIPHCzeroTwo(i,1)=xIPHCzeroTwo(2);
UphysIPHCzeroTwo(i,1)=uphysIPHCzeroTwo*(-1);
UpatIPHCzeroTwo(i,1)=upatIPHCzeroTwo;
UpatRealIPHCzeroTwo(i,1)=upatRealIPHCzeroTwo;
HealthIPHCzeroTwo(i,1)=healthIPHCzeroTwo;
UpatTreatedIPHCzeroTwo(i,1)=QIPHCzeroTwo;

end

%SUMMARY OF EACH GRAND GAME:

sumz1(j)=sum(zas1);
sumz2(j)=sum(zas2);

countfailureU1(j)=sum(countU1);
countfailureU2(j)=sum(countU2);
countfailureU3(j)=sum(countU3);
countfailureZ1(j)=sum(countZ1);
countfailureZ2(j)=sum(countZ2);
countfailureZ3(j)=sum(countZ3);
countfailureUZ2(j)=sum(countUZ2);

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countfailureUZ3(j)=sum(countUZ3);

eBenchline1=sort(eBenchline);
eIPHCzero1=sort(eIPHCzero);
eIPHCzeroTwo1=sort(eIPHCzeroTwo);
eBenchline1(eBenchline1==0)=[];
eIPHCzero1(eIPHCzero1==0)=[];
eIPHCzeroTwo1(eIPHCzeroTwo1==0)=[];

%MEAN EFFORT
MeanEffortBenchlineAll(j)=(1/k)*sum(eBenchline); %all physicians, also non treatment
MeanEffortIPHCzeroAll(j)=(1/k)*sum(eIPHCzero);
MeanEffortIPHCzeroTwoAll(j)=(1/k)*sum(eIPHCzeroTwo);

MeanEffortBenchline(j)=(1/length(eBenchline1))*sum(eBenchline1); %only treatment
MeanEffortIPHCzero(j)=(1/length(eIPHCzero1))*sum(eIPHCzero1);
MeanEffortIPHCzeroTwo(j)=(1/length(eIPHCzeroTwo1))*sum(eIPHCzeroTwo1);

sortedhealthBenchline=sort(HealthBenchline);
sortedhealthIPHCzero=sort(HealthIPHCzero);
sortedhealthIPHCzeroTwo=sort(HealthIPHCzeroTwo);
sortedhealthBenchline1=sort(HealthBenchline);
sortedhealthIPHCzero1=sort(HealthIPHCzero);
sortedhealthIPHCzeroTwo1=sort(HealthIPHCzeroTwo);
sortedhealthBenchline1(sortedhealthBenchline1==0) = []; %only treated patients
sortedhealthIPHCzero1(sortedhealthIPHCzero1==0) = [];
sortedhealthIPHCzeroTwo1(sortedhealthIPHCzeroTwo1==0) = [];

%MEAN HEALTH IMPROVEMENT FROM TREATMENT
MeanHealthBenchlineAll(j)=(1/k)*sum(HealthBenchline); %all patients
MeanHealthIPHCzeroAll(j)=(1/k)*sum(HealthIPHCzero);
MeanHealthIPHCzeroTwoAll(j)=(1/k)*sum(HealthIPHCzeroTwo);

MeanHealthBenchline(j)=(1/length(sortedhealthBenchline1))*sum(sortedhealthBenchline1); %
only treated patients
MeanHealthIPHCzero(j)=(1/length(sortedhealthIPHCzero1))*sum(sortedhealthIPHCzero1);
MeanHealthIPHCzeroTwo(j)=(1/length(sortedhealthIPHCzeroTwo1))*sum(
sortedhealthIPHCzeroTwo1);

%Health of bottom 10%
BottomHealthBenchline(j)=1/round(length(sortedhealthBenchline1))*sum(
sortedhealthBenchline1(1:round(length(sortedhealthBenchline1)/10))); %only treated
patients
BottomHealthIPHCzero(j)=1/round(length(sortedhealthIPHCzero1))*sum(sortedhealthIPHCzero1
(1:round(length(sortedhealthIPHCzero1)/10)));
BottomHealthIPHCzeroTwo(j)=1/round(length(sortedhealthIPHCzeroTwo1))*sum(
sortedhealthIPHCzeroTwo1(1:round(length(sortedhealthIPHCzero1)/10)));

BottomHealthBenchlineAll(j)=1/10*sum(sortedhealthBenchline(1:(k/10))); %all patients
BottomHealthIPHCzeroAll(j)=1/10*sum(sortedhealthIPHCzero(1:(k/10)));
BottomHealthIPHCzeroTwoAll(j)=1/10*sum(sortedhealthIPHCzeroTwo(1:(k/10)));

%Health of top 10%
TopHealthBenchlineAll(j)=1/10*sum(sortedhealthBenchline((9*k)/10:k)); %all patients
TopHealthIPHCzeroAll(j)=1/10*sum(sortedhealthIPHCzero((9*k)/10:k));
TopHealthIPHCzeroTwoAll(j)=1/10*sum(sortedhealthIPHCzeroTwo((9*k)/10:k));

if length(sortedhealthBenchline1)~=0
    TopHealthBenchline(j)=1/round(length(sortedhealthBenchline1))*sum(
sortedhealthBenchline1((9*round(length(sortedhealthBenchline1))/10:round(length(
sortedhealthBenchline1))));
else
    TopHealthBenchline(j)=0;
end
if length(sortedhealthIPHCzero1)~=0
    TopHealthIPHCzero(j)=1/round(length(sortedhealthIPHCzero1))*sum(sortedhealthIPHCzero1
((9*round(length(sortedhealthIPHCzero1))/10:round(length(sortedhealthIPHCzero1)
)));
else
    TopHealthIPHCzero(j)=0;
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end
if length(sortedhealthIPHCzeroTwo1) ~=0
    TopHealthIPHCzeroTwo(j)=1/round(length(sortedhealthIPHCzeroTwo1))*sum(
        sortedhealthIPHCzeroTwo1((9*round(length(sortedhealthIPHCzeroTwo1))/10:round(
            length(sortedhealthIPHCzeroTwo1))));
else
    TopHealthIPHCzeroTwo(j)=0;
end

%SOCIAL WELFARE
%utilitarian :
SoWelUtilitarianBenchline(j)= sum(UpatRealBenchline);
SoWelUtilitarianIPHCzero(j)=sum(UpatRealIPHCzero);
SoWelUtilitarianIPHCzeroTwo(j)=sum(UpatRealIPHCzeroTwo);

%utilitarian bottom 10%
sortedUtilitarianBenchline=sort(UpatRealBenchline);
sortedUtilitarianIPHCzero=sort(UpatRealIPHCzero);
sortedUtilitarianIPHCzeroTwo=sort(UpatRealIPHCzeroTwo);
BottomUtilitarianBenchline(j)=sum(sortedUtilitarianBenchline(1:(k/10)));
BottomUtilitarianIPHCzero(j)=sum(sortedUtilitarianIPHCzero(1:(k/10)));
BottomUtilitarianIPHCzeroTwo(j)=sum(sortedUtilitarianIPHCzeroTwo(1:(k/10)));

%utilitarian top 10%
TopUtilitarianBenchline(j)=sum(sortedUtilitarianBenchline((9*k)/10:k));
TopUtilitarianIPHCzero(j)=sum(sortedUtilitarianIPHCzero((9*k)/10:k));
TopUtilitarianIPHCzeroTwo(j)=sum(sortedUtilitarianIPHCzeroTwo((9*k)/10:k));

%utilitarian , treated only
sortedUtTreatedBenchline=sort(UpatTreatedBenchline);
sortedUtTreatedIPHCzero=sort(UpatTreatedIPHCzero);
sortedUtTreatedIPHCzeroTwo=sort(UpatTreatedIPHCzeroTwo);
sortedUtTreatedBenchline(sortedUtTreatedBenchline==0) = [];
sortedUtTreatedIPHCzero(sortedUtTreatedIPHCzero==0) = [];
sortedUtTreatedIPHCzeroTwo(sortedUtTreatedIPHCzeroTwo==0) = [];
TreatedUtilitarianBenchline(j)=sum(sortedUtTreatedBenchline);
TreatedUtilitarianIPHCzero(j)=sum(sortedUtTreatedIPHCzero);
TreatedUtilitarianIPHCzeroTwo(j)=sum(sortedUtTreatedIPHCzeroTwo);

%utilitarian bottom 10% treated only
UtilitarianTrBottBenchline(j)=1/round(length(sortedUtTreatedBenchline))*sum(
    sortedUtTreatedBenchline(1:round(length(sortedUtTreatedBenchline)/10)));
UtilitarianTrBottIPHCzero(j)=1/round(length(sortedUtTreatedIPHCzero))*sum(
    sortedUtTreatedIPHCzero(1:round(length(sortedUtTreatedIPHCzero)/10)));
UtilitarianTrBottIPHCzeroTwo(j)=1/round(length(sortedUtTreatedIPHCzeroTwo))*sum(
    sortedUtTreatedIPHCzeroTwo(1:round(length(sortedUtTreatedIPHCzeroTwo)/10)));

%utilitarian top 10% treated only
UtilitarianTrTopBenchline(j)=1/round(length(sortedUtTreatedBenchline))*sum(
    sortedUtTreatedBenchline((9*round(length(sortedUtTreatedBenchline)))/10:round(length(
    sortedUtTreatedBenchline))));
UtilitarianTrTopIPHCzero(j)=1/round(length(sortedUtTreatedIPHCzero))*sum(
    sortedUtTreatedIPHCzero((9*round(length(sortedUtTreatedIPHCzero)))/10:round(length(
    sortedUtTreatedIPHCzero))));
UtilitarianTrTopIPHCzeroTwo(j)=1/round(length(sortedUtTreatedIPHCzeroTwo))*sum(
    sortedUtTreatedIPHCzeroTwo((9*round(length(sortedUtTreatedIPHCzeroTwo)))/10:round(
    length(sortedUtTreatedIPHCzeroTwo))));

%Rawlsian
SoWelRawlsianBenchline(j)= min(UpatRealBenchline);
SoWelRawlsianIPHCzero(j)=min(UpatRealIPHCzero);
SoWelRawlsianIPHCzeroTwo(j)=min(UpatRealIPHCzeroTwo);

%Rawlsian treated only
SoWelRawlsianTREATEDBenchline(j)=min(sortedUtTreatedBenchline);
SoWelRawlsianTREATEDIPHCzero(j)=min(sortedUtTreatedIPHCzero);
SoWelRawlsianTREATEDIPHCzeroTwo(j)=min(sortedUtTreatedIPHCzeroTwo);
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%Bernoulli Nash

for i=1:k
    soWelBNBenchline=soWelBNBenchline*UpatRealBenchline(i);
end
SoWelBNBenchline(j)=soWelBNBenchline;

for i=1:k
    soWelBNIPHCzero=soWelBNIPHCzero*UpatRealIPHCzero(i);
end
SoWelBNIPHCzero(j)=soWelBNIPHCzero;

for i=1:k
    soWelBNIPHCzeroTwo=soWelBNIPHCzeroTwo*UpatRealIPHCzeroTwo(i);
end
SoWelBNIPHCzeroTwo(j)=soWelBNIPHCzeroTwo;
end

%RESULTS OF MONTE CARLO ESTIMATIONS
SoWelUtilitarianBenchlineMean = mean(SoWelUtilitarianBenchline)
SoWelUtilitarianIPHCzeroMean = mean(SoWelUtilitarianIPHCzero)
SoWelUtilitarianIPHCzeroTwoMean = mean(SoWelUtilitarianIPHCzeroTwo)
ErrorUtilitarianBenchline= sqrt(1/(length(SoWelUtilitarianBenchline)-1)*sum((
    SoWelUtilitarianBenchline-SoWelUtilitarianBenchlineMean).^2))
ErrorUtilitarianIPHCzero= sqrt(1/(length(SoWelUtilitarianIPHCzero)-1)*sum((
    SoWelUtilitarianIPHCzero-SoWelUtilitarianIPHCzeroMean).^2))
ErrorUtilitarianIPHCzeroTwo= sqrt(1/(length(SoWelUtilitarianIPHCzeroTwo)-1)*sum((
    SoWelUtilitarianIPHCzeroTwo-SoWelUtilitarianIPHCzeroTwoMean).^2))

SWTreatedUtilitarianBenchline = mean(TreatedUtilitarianBenchline)
SWTreatedUtilitarianIPHCzero = mean(TreatedUtilitarianIPHCzero)
SWTreatedUtilitarianIPHCzeroTwo = mean(TreatedUtilitarianIPHCzeroTwo)
ErrorTreatedUtilitarianBenchline=sqrt(1/(length(TreatedUtilitarianBenchline)-1)*sum((
    TreatedUtilitarianBenchline-SWTreatedUtilitarianBenchline).^2))
ErrorTreatedUtilitarianIPHCzero=sqrt(1/(length(TreatedUtilitarianIPHCzero)-1)*sum((
    TreatedUtilitarianIPHCzero-SWTreatedUtilitarianIPHCzero).^2))
ErrorTreatedUtilitarianIPHCzeroTwo=sqrt(1/(length(TreatedUtilitarianIPHCzeroTwo)-1)*sum((
    TreatedUtilitarianIPHCzeroTwo-SWTreatedUtilitarianIPHCzeroTwo).^2))

SoWelUtilitarianBenchlineMeanBOTTOM = mean(BottomUtilitarianBenchline)
SoWelUtilitarianIPHCzeroMeanBOTTOM = mean(BottomUtilitarianIPHCzero)
SoWelUtilitarianIPHCzeroTwoMeanBOTTOM = mean(BottomUtilitarianIPHCzeroTwo)
ErrorBottomUtilitarianBenchline=sqrt(1/(length(BottomUtilitarianBenchline)-1)*sum((
    BottomUtilitarianBenchline-SoWelUtilitarianBenchlineMeanBOTTOM).^2))
ErrorBottomUtilitarianIPHCzero=sqrt(1/(length(BottomUtilitarianIPHCzero)-1)*sum((
    BottomUtilitarianIPHCzero-SoWelUtilitarianIPHCzeroMeanBOTTOM).^2))
ErrorBottomUtilitarianIPHCzeroTwo=sqrt(1/(length(BottomUtilitarianIPHCzeroTwo)-1)*sum((
    BottomUtilitarianIPHCzeroTwo-SoWelUtilitarianIPHCzeroTwoMeanBOTTOM).^2))

SWTreatedUtilitarianBottomBenchline = mean(UtilitarianTrBottBenchline)
SWTreatedUtilitarianBottomIPHCzero = mean(UtilitarianTrBottIPHCzero)
SWTreatedUtilitarianBottomIPHCzeroTwo = mean(UtilitarianTrBottIPHCzeroTwo)
ErrorTrBottomUtilitarianBenchline=sqrt(1/(length(UtilitarianTrBottBenchline)-1)*sum((
    UtilitarianTrBottBenchline-SWTreatedUtilitarianBottomBenchline).^2))
ErrorTrBottomUtilitarianIPHCzero=sqrt(1/(length(UtilitarianTrBottIPHCzero)-1)*sum((
    UtilitarianTrBottIPHCzero-SWTreatedUtilitarianBottomIPHCzero).^2))
ErrorTrBottomUtilitarianIPHCzeroTwo=sqrt(1/(length(UtilitarianTrBottIPHCzeroTwo)-1)*sum((
    UtilitarianTrBottIPHCzeroTwo-SWTreatedUtilitarianBottomIPHCzeroTwo).^2))

SoWelUtilitarianBenchlineMeanTop = mean(TopUtilitarianBenchline)
SoWelUtilitarianIPHCzeroMeanTop = mean(TopUtilitarianIPHCzero)
SoWelUtilitarianIPHCzeroTwoMeanTop = mean(TopUtilitarianIPHCzeroTwo)
ErrorTopUtilitarianBenchline=sqrt(1/(length(TopUtilitarianBenchline)-1)*sum((
    TopUtilitarianBenchline-SoWelUtilitarianBenchlineMeanTop).^2))
ErrorTopUtilitarianIPHCzero=sqrt(1/(length(TopUtilitarianIPHCzero)-1)*sum((
    TopUtilitarianIPHCzero-SoWelUtilitarianIPHCzeroMeanTop).^2))
ErrorTopUtilitarianIPHCzeroTwo=sqrt(1/(length(TopUtilitarianIPHCzeroTwo)-1)*sum((
    TopUtilitarianIPHCzeroTwo-SoWelUtilitarianIPHCzeroTwoMeanTop).^2))

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SWTreatedUtilitarianTopBenchline = mean(UtilitarianTrTopBenchline)
SWTreatedUtilitarianTopIPHCzero = mean(UtilitarianTrTopIPHCzero)
SWTreatedUtilitarianTopIPHCzeroTwo = mean(UtilitarianTrTopIPHCzeroTwo)
ErrorTrTopUtilitarianBenchline=sqrt(1/(length(UtilitarianTrTopBenchline)-1)*sum((
  UtilitarianTrTopBenchline-SWTreatedUtilitarianTopBenchline).^2))
ErrorTrTopUtilitarianIPHCzero=sqrt(1/(length(UtilitarianTrTopIPHCzero)-1)*sum((
  UtilitarianTrTopIPHCzero-SWTreatedUtilitarianTopIPHCzero).^2))
ErrorTrTopUtilitarianIPHCzeroTwo=sqrt(1/(length(UtilitarianTrTopIPHCzeroTwo)-1)*sum((
  UtilitarianTrTopIPHCzeroTwo-SWTreatedUtilitarianTopIPHCzeroTwo).^2))

SoWelUtilitarianBenchlineRatio=SoWelUtilitarianBenchlineMeanBOTTOM/
  SoWelUtilitarianBenchlineMeanTop
SoWelUtilitarianIPHCzeroRatio=SoWelUtilitarianIPHCzeroMeanBOTTOM/
  SoWelUtilitarianIPHCzeroMeanTop
SoWelUtilitarianIPHCzeroTwoRatio=SoWelUtilitarianIPHCzeroTwoMeanBOTTOM/
  SoWelUtilitarianIPHCzeroTwoMeanTop
ErrorRatioUtilitarianBenchline=sqrt((ErrorBottomUtilitarianBenchline/
  SoWelUtilitarianBenchlineMeanBOTTOM)^2+(ErrorTopUtilitarianBenchline/
  SoWelUtilitarianBenchlineMeanTop)^2)*SoWelUtilitarianBenchlineRatio
ErrorRatioUtilitarianIPHCzero=sqrt((ErrorBottomUtilitarianIPHCzero/
  SoWelUtilitarianIPHCzeroMeanBOTTOM)^2+(ErrorTopUtilitarianIPHCzero/
  SoWelUtilitarianIPHCzeroMeanTop)^2)*SoWelUtilitarianIPHCzeroRatio
ErrorRatioUtilitarianIPHCzeroTwo=sqrt((ErrorBottomUtilitarianIPHCzeroTwo/
  SoWelUtilitarianIPHCzeroTwoMeanBOTTOM)^2+(ErrorTopUtilitarianIPHCzeroTwo/
  SoWelUtilitarianIPHCzeroTwoMeanTop)^2)*SoWelUtilitarianIPHCzeroTwoRatio

SWTreatedUtilitarianBenchlineRatio=SWTreatedUtilitarianBottomBenchline/
  SWTreatedUtilitarianTopBenchline
SWTreatedUtilitarianIPHCzeroRatio=SWTreatedUtilitarianBottomIPHCzero/
  SWTreatedUtilitarianTopIPHCzero
SWTreatedUtilitarianIPHCzeroTwoRatio=SWTreatedUtilitarianBottomIPHCzeroTwo/
  SWTreatedUtilitarianTopIPHCzeroTwo
ErrorRatioUtilitarianTRBenchline=sqrt((ErrorTrBottomUtilitarianBenchline/
  SWTreatedUtilitarianBottomBenchline)^2+(ErrorTrTopUtilitarianBenchline/
  SWTreatedUtilitarianTopBenchline)^2)*SWTreatedUtilitarianBenchlineRatio
ErrorRatioUtilitarianTRIPHCzero=sqrt((ErrorTrBottomUtilitarianIPHCzero/
  SWTreatedUtilitarianBottomIPHCzero)^2+(ErrorTrTopUtilitarianIPHCzero/
  SWTreatedUtilitarianTopIPHCzero)^2)*SWTreatedUtilitarianIPHCzeroRatio
ErrorRatioUtilitarianTRIPHCzeroTwo=sqrt((ErrorTrBottomUtilitarianIPHCzeroTwo/
  SWTreatedUtilitarianBottomIPHCzeroTwo)^2+(ErrorTrTopUtilitarianIPHCzeroTwo/
  SWTreatedUtilitarianTopIPHCzeroTwo)^2)*SWTreatedUtilitarianIPHCzeroTwoRatio

SoWelRawlsianBenchlineMean = mean(SoWelRawlsianBenchline)
SoWelRawlsianIPHCzeroMean = mean(SoWelRawlsianIPHCzero)
SoWelRawlsianIPHCzeroTwoMean = mean(SoWelRawlsianIPHCzeroTwo)
ErrorSoWelRawlsianBenchline = sqrt(1/(length(SoWelRawlsianBenchline)-1)*sum((
  SoWelRawlsianBenchline-SoWelRawlsianBenchlineMean).^2))
ErrorSoWelRawlsianIPHCzero = sqrt(1/(length(SoWelRawlsianIPHCzero)-1)*sum((
  SoWelRawlsianIPHCzero-SoWelRawlsianIPHCzeroMean).^2))
ErrorSoWelRawlsianIPHCzeroTwo = sqrt(1/(length(SoWelRawlsianIPHCzeroTwo)-1)*sum((
  SoWelRawlsianIPHCzeroTwo-SoWelRawlsianIPHCzeroTwoMean).^2))

SoWelBNBenchlineMean = mean(SoWelBNBenchline)
SoWelBNIPHCzeroMean = mean(SoWelBNIPHCzero)
SoWelBNIPHCzeroTwoMean = mean(SoWelBNIPHCzeroTwo)
ErrorSoWelBNBenchline = sqrt(1/(length(SoWelBNBenchline)-1)*sum((SoWelBNBenchline-
  SoWelBNBenchlineMean).^2))
ErrorSoWelBNIPHCzero = sqrt(1/(length(SoWelBNIPHCzero)-1)*sum((SoWelBNIPHCzero-
  SoWelBNIPHCzeroMean).^2))
ErrorSoWelBNIPHCzeroTwo = sqrt(1/(length(SoWelBNIPHCzeroTwo)-1)*sum((SoWelBNIPHCzeroTwo-
  SoWelBNIPHCzeroTwoMean).^2))

SWTreatedRawlsianBenchline=mean(SoWelRawlsianTREATEDBenchline)
SWTreatedRawlsianIPHCzero=mean(SoWelRawlsianTREATEDIPHCzero)
SWTreatedRawlsianIPHCzeroTwo=mean(SoWelRawlsianTREATEDIPHCzeroTwo)
ErrorSWTreatedRawlsianBenchline = sqrt(1/(length(SoWelRawlsianTREATEDBenchline)-1)*sum((
  SoWelRawlsianTREATEDBenchline-SWTreatedRawlsianBenchline).^2))
ErrorSWTreatedRawlsianIPHCzero = sqrt(1/(length(SoWelRawlsianTREATEDIPHCzero)-1)*sum((
  SoWelRawlsianTREATEDIPHCzero-SWTreatedRawlsianIPHCzero).^2))
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ErrorSWTreatedRawlsianIPHCzeroTwo = sqrt(1/(length(SoWelRawlsianTREATEDIPHCzeroTwo)-1)*sum((
  SoWelRawlsianTREATEDIPHCzeroTwo-SWTreatedRawlsianIPHCzeroTwo).^2))

HealthBenchlineMEANAll = mean(MeanHealthBenchlineAll)
HealthIPHCzeroMEANAll = mean(MeanHealthIPHCzeroAll)
HealthIPHCzeroTwoMEANAll = mean(MeanHealthIPHCzeroTwoAll)
ErrorHealthBenchlineAll=sqrt(1/(length(MeanHealthBenchlineAll)-1)*sum((MeanHealthBenchlineAll
  -HealthBenchlineMEANAll).^2))
ErrorHealthIPHCzeroAll=sqrt(1/(length(MeanHealthIPHCzeroAll)-1)*sum((MeanHealthIPHCzeroAll-
  HealthIPHCzeroMEANAll).^2))
ErrorHealthIPHCzeroTwoAll=sqrt(1/(length(MeanHealthIPHCzeroTwoAll)-1)*sum((
  MeanHealthIPHCzeroTwoAll-HealthIPHCzeroTwoMEANAll).^2))

HealthBenchlineMEAN = mean(MeanHealthBenchline)
HealthIPHCzeroMEAN = mean(MeanHealthIPHCzero)
HealthIPHCzeroTwoMEAN = mean(MeanHealthIPHCzeroTwo)
ErrorHealthBenchline=sqrt(1/(length(MeanHealthBenchline)-1)*sum((MeanHealthBenchline-
  HealthBenchlineMEAN).^2))
ErrorHealthIPHCzero=sqrt(1/(length(MeanHealthIPHCzero)-1)*sum((MeanHealthIPHCzero-
  HealthIPHCzeroMEAN).^2))
ErrorHealthIPHCzeroTwo=sqrt(1/(length(MeanHealthIPHCzeroTwo)-1)*sum((MeanHealthIPHCzeroTwo-
  HealthIPHCzeroTwoMEAN).^2))

HealthBenchlineBOTTOM = mean(BottomHealthBenchline)
HealthIPHCzeroBOTTOM = mean(BottomHealthIPHCzero)
HealthIPHCzeroTwoBOTTOM = mean(BottomHealthIPHCzeroTwo)
ErrorHealthBenchlineBOTTOM=sqrt(1/(length(BottomHealthBenchline)-1)*sum((
  BottomHealthBenchline-HealthBenchlineBOTTOM).^2))
ErrorHealthIPHCzeroBOTTOM=sqrt(1/(length(BottomHealthIPHCzero)-1)*sum((BottomHealthIPHCzero-
  HealthIPHCzeroBOTTOM).^2))
ErrorHealthIPHCzeroTwoBOTTOM=sqrt(1/(length(BottomHealthIPHCzeroTwo)-1)*sum((
  BottomHealthIPHCzeroTwo-HealthIPHCzeroTwoBOTTOM).^2))

HealthBenchlineBOTTOMAll = mean(BottomHealthBenchlineAll)
HealthIPHCzeroBOTTOMAll = mean(BottomHealthIPHCzeroAll)
HealthIPHCzeroTwoBOTTOMAll = mean(BottomHealthIPHCzeroTwoAll)
ErrorHealthBenchlineBOTTOMAll=sqrt(1/(length(BottomHealthBenchlineAll)-1)*sum((
  BottomHealthBenchlineAll-HealthBenchlineBOTTOMAll).^2))
ErrorHealthIPHCzeroBOTTOMAll=sqrt(1/(length(BottomHealthIPHCzeroAll)-1)*sum((
  BottomHealthIPHCzeroAll-HealthIPHCzeroBOTTOMAll).^2))
ErrorHealthIPHCzeroTwoBOTTOMAll=sqrt(1/(length(BottomHealthIPHCzeroTwoAll)-1)*sum((
  BottomHealthIPHCzeroTwoAll-HealthIPHCzeroTwoBOTTOMAll).^2))

HealthBenchlineTop = mean(TopHealthBenchline)
HealthIPHCzeroTop = mean(TopHealthIPHCzero)
HealthIPHCzeroTwoTop = mean(TopHealthIPHCzeroTwo)
ErrorHealthBenchlineTop=sqrt(1/(length(TopHealthBenchline)-1)*sum((TopHealthBenchline-
  HealthBenchlineTop).^2))
ErrorHealthIPHCzeroTop=sqrt(1/(length(TopHealthIPHCzero)-1)*sum((TopHealthIPHCzero-
  HealthIPHCzeroTop).^2))
ErrorHealthIPHCzeroTwoTop=sqrt(1/(length(TopHealthIPHCzeroTwo)-1)*sum((TopHealthIPHCzeroTwo-
  HealthIPHCzeroTwoTop).^2))

HealthBenchlineTopAll = mean(TopHealthBenchlineAll)
HealthIPHCzeroTopAll = mean(TopHealthIPHCzeroAll)
HealthIPHCzeroTwoTopAll = mean(TopHealthIPHCzeroTwoAll)
ErrorHealthBenchlineTopAll=sqrt(1/(length(TopHealthBenchlineAll)-1)*sum((
  TopHealthBenchlineAll-HealthBenchlineTopAll).^2))
ErrorHealthIPHCzeroTopAll=sqrt(1/(length(TopHealthIPHCzeroAll)-1)*sum((TopHealthIPHCzeroAll-
  HealthIPHCzeroTopAll).^2))
ErrorHealthIPHCzeroTwoTopAll=sqrt(1/(length(TopHealthIPHCzeroTwoAll)-1)*sum((
  TopHealthIPHCzeroTwoAll-HealthIPHCzeroTwoTopAll).^2))

HealthBenchlineRatio=HealthBenchlineBOTTOM/HealthBenchlineTop
HealthIPHCzeroRatio=HealthIPHCzeroBOTTOM/HealthIPHCzeroTop
HealthIPHCzeroTwoRatio=HealthIPHCzeroTwoBOTTOM/HealthIPHCzeroTwoTop
ErrorRatioBenchline=sqrt((ErrorHealthBenchlineBOTTOM/HealthBenchlineBOTTOM)^2+(
  ErrorHealthBenchlineTop/HealthBenchlineTop)^2)*HealthBenchlineRatio
ErrorRatioIPHCzero=sqrt((ErrorHealthIPHCzeroBOTTOM/HealthIPHCzeroBOTTOM)^2+(
  ErrorHealthIPHCzeroTop/HealthIPHCzeroTop)^2)*HealthIPHCzeroRatio
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ErrorRatioIPHCzeroTwo=sqrt (( ErrorHealthIPHCzeroTwoBOTTOM/HealthIPHCzeroTwoBOTTOM)^2+(
    ErrorHealthIPHCzeroTwoTop/HealthIPHCzeroTwoTop)^2)*HealthIPHCzeroTwoRatio

HealthBenchlineRatioAll=HealthBenchlineBOTTOMAll/HealthBenchlineTopAll
HealthIPHCzeroRatioAll=HealthIPHCzeroBOTTOMAll/HealthIPHCzeroTopAll
HealthIPHCzeroTwoRatioAll=HealthIPHCzeroTwoBOTTOMAll/HealthIPHCzeroTwoTopAll
ErrorRatioBenchlineAll=sqrt (( ErrorHealthBenchlineBOTTOMAll/HealthBenchlineBOTTOMAll)^2+(
    ErrorHealthBenchlineTopAll/HealthBenchlineTopAll)^2)*HealthBenchlineRatioAll
ErrorRatioIPHCzeroAll=sqrt (( ErrorHealthIPHCzeroBOTTOMAll/HealthIPHCzeroBOTTOMAll)^2+(
    ErrorHealthIPHCzeroTopAll/HealthIPHCzeroTopAll)^2)*HealthIPHCzeroRatioAll
ErrorRatioIPHCzeroTwoAll=sqrt (( ErrorHealthIPHCzeroTwoBOTTOMAll/HealthIPHCzeroTwoBOTTOMAll)
    ^2+(ErrorHealthIPHCzeroTwoTopAll/HealthIPHCzeroTwoTopAll)^2)*HealthIPHCzeroTwoRatioAll

EffortBenchlineMEANAll =mean( MeanEffortBenchlineAll)
EffortIPHCzeroMEANAll = mean( MeanEffortIPHCzeroAll)
EffortIPHCzeroTwoMEANAll = mean( MeanEffortIPHCzeroTwoAll)
ErrorBenchlineAll=sqrt (1/(length ( MeanEffortBenchlineAll) -1)*sum(( MeanEffortBenchlineAll-
    EffortBenchlineMEANAll).^2))
ErrorIPHCzeroAll=sqrt (1/(length ( MeanEffortIPHCzeroTwoAll) -1)*sum(( MeanEffortIPHCzeroAll-
    EffortIPHCzeroMEANAll).^2))
ErrorIPHCzeroTwoAll=sqrt (1/(length ( MeanEffortIPHCzeroTwoAll) -1)*sum(( MeanEffortIPHCzeroTwoAll-
    EffortIPHCzeroTwoMEANAll).^2))

EffortBenchlineMEAN =mean( MeanEffortBenchline)
EffortIPHCzeroMEAN = mean( MeanEffortIPHCzero)
EffortIPHCzeroTwoMEAN = mean( MeanEffortIPHCzeroTwo)
ErrorBenchline=sqrt (1/(length ( MeanEffortBenchline) -1)*sum(( MeanEffortBenchline-
    EffortBenchlineMEAN).^2))
ErrorIPHCzero=sqrt (1/(length ( MeanEffortIPHCzero) -1)*sum(( MeanEffortIPHCzero-
    EffortIPHCzeroMEAN).^2))
ErrorIPHCzeroTwo=sqrt (1/(length ( MeanEffortIPHCzeroTwo) -1)*sum(( MeanEffortIPHCzeroTwo-
    EffortIPHCzeroTwoMEAN).^2))

%Counts contract failures
totalzIPHCzero=sum(sumz1)/(k*n)
totalzIPHCzeroTwo=sum(sumz2)/(k*n)
totalcountU1=sum(countfailureU1)/(k*n)
totalcountU2=sum(countfailureU2)/(k*n)
totalcountU3=sum(countfailureU3)/(k*n)
totalcountZ1=sum(countfailureZ1)/(k*n)
totalcountZ2=sum(countfailureZ2)/(k*n)
totalcountZ3=sum(countfailureZ3)/(k*n)
totalfailureUZ2=sum(countfailureUZ2)/(k*n)
totalfailureUZ3=sum(countfailureUZ3)/(k*n)
toc

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                 %
% Optimization using fmincon ,                                     %
% Benchline                                                       %
%                                                                 %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [e,fval,Upat, UpatReal, Health] = benchline()
global htilde tnorm a h constr

%starting point 1
x0 = 0.5; % Starting guess at the solution
lb = 0;
ub = 1;
A=[];
b=[];
Aeq=[];
beq=[];

options=optimset('Algorithm','interior-point');
if constr==1
[e1, fval1] = fmincon(@objective,x0,A,b,Aeq,beq,lb,ub,@mycon,options);
end
if constr==0

```


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```

[e1, fval1] = fmincon(@objective,x0,A,b,Aeq,beq,lb,ub,'', options);
end

%starting point 2
x0 = 0.9; % Starting guess at the solution
lb = 0;
ub = 1;
A=[];
b=[];
Aeq=[];
beq=[];

options=optimset('Algorithm','interior-point');
if constr==1
[e2, fval2] = fmincon(@objective,x0,A,b,Aeq,beq,lb,ub,@mycon, options);
end
if constr==0
[e2, fval2] = fmincon(@objective,x0,A,b,Aeq,beq,lb,ub,'', options);
end

%Chooses the min of 1 and 2
if fval1<fval2
e=e1;
fval=fval1;
else
e=e2;
fval=fval2;
end

% Upat= (htilde^(0.25)*tnorm^(0.25)*0.5^(0.25))^(0.7)+(a)^(0.5);
% UpatReal=(h^(0.25)*tnorm^(0.25)*e^(0.25))^(0.7)+(a)^(0.5);
% Health=h^(0.25)*tnorm^(0.25)*e^(0.25);

%alternative health function
Upat= (htilde^(0.4)*tnorm^(0.3)*0.5^(0.2))^(0.2)+(a)^(0.5);
UpatReal=(h^(0.4)*tnorm^(0.3)*e^(0.2))^(0.2)+(a)^(0.5);
Health=h^(0.4)*tnorm^(0.3)*e^(0.2);

end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% Optimization using fmincon,
% IPHC = 0
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function[x,fval,Upat2,UpatReal,Health]=IPHCzero()
global r h htilde tnorm a atilde constr;

%Starting point 1
x0 = [0.1, 0.1]; % Starting guess at the solution
lb = [0,0];
ub = [1,atilde];%OBS atilde a ad vera,
A=[];
b=[];
Aeq=[];
beq=[];
options=optimset('Algorithm','interior-point');
if constr==1
[x1, fval1] = fmincon(@objective2,x0,A,b,Aeq,beq,lb,ub,@mycon2, options);
end
if constr==0
[x1, fval1] = fmincon(@objective2,x0,A,b,Aeq,beq,lb,ub,'', options);
end

%Starting point 2
x0 = [0.8, 0.8]; % Starting guess at the solution
lb = [0,0];
ub = [1,atilde];%OBS atilde a ad vera,

```

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```

A=[];
b=[];
Aeq=[];
beq=[];

options=optimset('Algorithm','interior-point');
if constr==1
[x2, fval2] = fmincon(@objective2,x0,A,b,Aeq,beq,lb,ub,@mycon2,options);
end
if constr==0
[x2, fval2] = fmincon(@objective2,x0,A,b,Aeq,beq,lb,ub,'',options);
end

%Chooses the smaller value
if fval1<fval2
x=x1;
fval=fval1;
else
x=x2;
fval=fval2;
end

%sets disutility if IPHC exceeds wealth
if a-x(2) >= 0
ERS=sqrt(a-x(2));
else
ERS=-sqrt(x(2)-a);
end

% Upat2 =(htilde^(0.25)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.25)*0.5^(0.25))^(0.7)+ERS-(1-r)*(x(2)-0)^(r);
% UpatReal=(h^(0.25)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)+ERS-(1-r)*(x(2)-0)^(r);
% Health=h^(0.25)*tnorm^(0.25)*x(1)^(0.25);

%alternative health function
Upat2 =(htilde^(0.4)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.3)*0.5^(0.2))^(0.2)+ERS-(1-r)*(x(2)-0)^(r);
UpatReal=(h^(0.4)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.3)*x(1)^(0.2))^(0.2)+ERS-(1-r)*(x(2)-0)^(r);
Health=h^(0.4)*tnorm^(0.3)*x(1)^(0.2);
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% Optimization using fmincon,
% IPHC > 0
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function[x,fval,Upat3,UpatReal,Health]=IPHCzerotwo()
global r znorm h a atilde htilde tnorm constr;

%Calculates optimal value with starting point 1
x0 = [0.1, 0.1]; % Starting guess at the solution
lb = [0,znorm];
ub = [1,atilde];%obs atilde a ad vera
A=[];
b=[];
Aeq=[];
beq=[];

options=optimset('Algorithm','interior-point');
if constr==1
[x1, fval1] = fmincon(@objective3,x0,A,b,Aeq,beq,lb,ub,@mycon3,options);
end
if constr==0
[x1, fval1] = fmincon(@objective3,x0,A,b,Aeq,beq,lb,ub,'',options);

```

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```

end

%Calculates optimal value with starting point 2
x0 = [0.9, 0.9]; % Starting guess at the solution
lb = [0, znorm];
ub = [1, atilde]; % obs atilde a ad vera
A=[];
b=[];
Aeq=[];
beq=[];

options=optimset('Algorithm','interior-point');
if constr==1
[x2, fval2] = fmincon(@objective3,x0,A,b,Aeq,beq,lb,ub,@mycon3,options);
end
if constr==0
[x2, fval2] = fmincon(@objective3,x0,A,b,Aeq,beq,lb,ub,[],options);
end

%Chooses the min of optimization with starting points 1 and 2
if fval1<fval2
x=x1;
fval=fval1;
else
x=x2;
fval=fval2;
end

%Sets disutility if IPHC exceeds wealth
if a-x(2) >= 0
ERS=sqrt(a-x(2));
else
ERS=(-1)*sqrt(x(2)-a);
end

%
% Upat3 =(htilde^(0.25)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.25)*0.5^(0.25))^(0.7)+ERS
-(1-r)*(x(2)-znorm)^(r);
% UpatReal=(h^(0.25)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)+ERS
-(1-r)*(x(2)-znorm)^(r);
% Health=h^(0.25)*tnorm^(0.25)*x(1)^(0.25);

% %alternative health function
Upat3 =(htilde^(0.4)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.3)*0.5^(0.2))^(0.2)+ERS-(1-r)
)*(x(2)-znorm)^(r);
UpatReal=(h^(0.4)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.3)*x(1)^(0.2))^(0.2)+ERS-(1-r)
*(x(2)-znorm)^(r);
Health=h^(0.4)*tnorm^(0.3)*x(1)^(0.2);

end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% OBJECTIVE FUNCTION, benchline
% This is the objective function of the physician optimization in the
% benchline version of the model.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function f = objective(e)
global q
global h
global tnorm
global y

%f = -q*(h^(0.25)*tnorm^(0.25)*e^(0.25))^(0.7)-(y)^(0.5)+0.1*e^(0.5);

%alternative Health function
f = -q*(h^(0.4)*tnorm^(0.3)*e^(0.2))^(0.2)-(y)^(0.5)+0.1*e^(0.5);

```

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```

end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% OBJECTIVE FUNCTION, IPHC = 0.
% This is the objective function of the physician optimization when IPHC.%
% equals zero.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function f = objective2(x)
global g q h y tnorm w;
%f = -q*(h.^(0.25)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)-(y+x(2))
    ^ (0.5)+w*(1-g)*(x(2)-0)^(g)+0.1*x(1)^(0.5);

%alternative health function
f = -q*(h.^(0.4)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.3)*x(1)^(0.2))^(0.2)-(y+x(2))^(0.5)+
    w*(1-g)*(x(2)-0)^(g)+0.1*x(1)^(0.5);

end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% OBJECTIVE FUNCTION, IPHC > 0.
% This is the objective function of the physician optimization when IPHC.%
% is larger than zero.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function f = objective3(x)
global g q h y tnorm znorm w;
%f = -q*(h.^(0.25)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)-(y+x(2))
    ^ (0.5)+w*(1-g)*(x(2)-znorm)^(g)+0.1*x(1)^(0.5);

%alternative Health function
f = -q*(h.^(0.4)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.3)*x(1)^(0.2))^(0.2)-(y+x(2))
    ^ (0.5)+w*(1-g)*(x(2)-znorm)^(g)+0.1*x(1)^(0.5);

end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% CONSTRAINT: E_phys(U_pat)>E(res.utility)
% Benchline
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [c1, ceq] = mycon(e)
global h atilde tnorm resutility;

% if resutility==1
% %Nonzero reservation utility:
% c1 = -(h^(0.25)*tnorm^(0.25)*e^(0.25))^(0.7)-(atilde)^(0.5)+(atilde)^0.5;
% end
%
% if resutility==0
% %Zero reservation utility:
% c1 = -(h^(0.25)*tnorm^(0.25)*e^(0.25))^(0.7)-(atilde)^(0.5);
% end

%alternative health functon
if resutility==1
%Nonzero reservation utility:
c1 = -(h^(0.4)*tnorm^(0.3)*e^(0.2))^(0.2)-(atilde)^(0.5)+(atilde)^0.5;
end

if resutility==0
%Zero reservation utility:
c1 = -(h^(0.4)*tnorm^(0.3)*e^(0.2))^(0.2)-(atilde)^(0.5);
end

```

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```

end

ceq=[];
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% CONSTRAINT: E_phys(U_pat)>E(res.utility)
% IPHC = 0
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [c, ceq] = mycon2(x)
global r atilde h tnorm resutility r1 r2;

% if resutility == 1
% % nonzero reservation utility:
% c = -(h^(0.25)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)-(atilde-x(2))
%       ^ (0.5)+(r1/(r1+r2))*(x(2)-0)^(0.5)+(atilde)^0.5;
% end
%
% if resutility ==0
% % zero reservation utility:
% c = -(h^(0.25)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)-(atilde-x(2))
%       ^ (0.5)+(r1/(r1+r2))*(x(2)-0)^(0.5);
% end

% alternative health function
if resutility == 1
%nonzero reservation utility:
c = -(h^(0.4)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.3)*x(1)^(0.2))^(0.2)-(atilde-x(2))
    ^ (0.5)+(r1/(r1+r2))*(x(2)-0)^(0.5)+(atilde)^0.5;
end

if resutility ==0
%zero reservation utility:
c = -(h^(0.4)*(sqrt((1-tnorm^2)*(x(2)-0)+tnorm^2))^(0.3)*x(1)^(0.25))^(0.2)-(atilde-x(2))
    ^ (0.5)+(r1/(r1+r2))*(x(2)-0)^(0.5);
end
ceq=[];
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% CONSTRAINT: E_phys(U_pat)>E(res.utility)
% IPHC > 0
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [c, ceq] = mycon3(x)
global h tnorm atilde znorm resutility r1 r2

% if resutility == 1
% %nonzero reservation utility:
% c = -(h^(0.25)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)-(atilde-x
%       (2))^(0.5)+(r1/(r1+r2))*(x(2)-znorm)^(0.5)+(atilde)^0.5;
% end
%
% if resutility ==0
% %zero reservation utility:
% c = -(h^(0.25)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.25)*x(1)^(0.25))^(0.7)-(atilde-x
%       (2))^(0.5)+(r1/(r1+r2))*(x(2)-znorm)^(0.5);
% end

%alternative health function
if resutility == 1
%nonzero reservation utility:

```

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```
c = -(h^(0.4)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.3)*x(1)^(0.2))^(0.)-(atilde-x(2))
      ^ (0.5)+(r1/(r1+r2))*(x(2)-znorm)^(0.5)+(atilde)^0.5;
end

if resutility ==0
%zero reservation utility:
c = -(h^(0.4)*(sqrt((1-tnorm^2)*(x(2)-znorm)+tnorm^2))^(0.3)*x(1)^(0.2))^(0.2)-(atilde-x(2))
      ^ (0.5)+(r1/(r1+r2))*(x(2)-znorm)^(0.5);
end

ceq=[];
end

\end{verbatim}
```

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