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## Identification of supplier-induced demand: What kind of consumer information matters?

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**Identification of Supplier-induced Demand  
What kind of consumer information matters?**

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**DISCUSSION PAPERS**

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# Identification of Supplier-induced Demand

## What kind of consumer information matters?\*

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February 4, 2013

### **Abstract**

The focus of the present study is on consumer health information in relation to supplier induced demand (SID). We argue that a comparison between medical professionals and non-medical professionals fails to identify demand inducement. Using a new information measure based on questions of the Swiss Health Survey, we estimate a Poisson hurdle model for office visits and the length of stay in hospitals. We find that information has a negative effect on health care utilization. Consequently, we find evidence for SID while our findings support the argument that the profession cannot be used to identify demand inducement.

JEL-Classification: I11, I18, C24

Keywords: Supplier-Induced Demand; Consumer Information; Poisson-hurdle model

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## 1 Introduction

The supplier-induced demand (SID) hypothesis dates back to the seminal work of Arrow (1963) on consumer information in the health care market and the insight discussed by e.g. Feldstein (1970), Evans (1974), and Fuchs (1978) that conventional supply and demand models are not applicable to the health care market. According to the inducement hypothesis, health care providers are suspected to exploit their information advantage for financial gains while acting as agents for their patients. As a result, the uninformed patients consume medical services which they would refuse if they had the same medical expertise as e.g. their physician. However, there is no consensus among health economists as to whether the information asymmetry at hand leads to seriously erratic behaviour of health care providers (see Labelle et al., 1994), even though a majority of economists and physicians suspect health care providers to induce demand (McGuire, 2000). Moreover, while the central issue is easily comprehensible in theory, testing the SID hypothesis turns out to be quite difficult in practice. In addition, Dranove and Wehner (1993) impressively show that the widely used two-stage least squares approach fails to identify SID due to unsuitable instruments. But especially due to the unsettled discussion and the possibly far-reaching policy implications, finding evidence for or against the inducement hypothesis is still an important issue.

Besides the comparison of physicians by their type of contract as for example in Grytten and Sorensen (1999, 2001) and studies based on time-varying covariates like in Van Doorslaer and Geurts (1987), one of the most promising approaches relies on differences in the information level of the patients. Since the SID hypothesis is based on the information asymmetry between patients and physicians, this idea directly links the theory and the empirical approach. Commonly, information is measured by the occupation, i.e. individuals working in the health care sector are assumed to have more information on health services. Therefore, they are supposed to be less prone to demand inducement. Using medical occupation as explanatory variable, Bunker and Brown (1974) as well as Hay and Leahy (1982) do not find evidence for the inducement hypothesis. Contrary, Domenighetti et al. (1993) show that the demand for several surgical services is significantly smaller among physicians compared with the general population. However, it is somehow questionable whether medical occupation merely measures consumer information in line with the SID hypothesis since working in the health care sector might e.g. decrease the individual's price of medical care or

its attitude towards health. In that case, shifts in the demand related to the individual's occupation cannot be taken as evidence for or against the inducement hypothesis.

The focus of the present study is to examine whether SID exists for health care services in Switzerland, i.e. physicians and hospitals. We argue that medical occupation is an inaccurate measure of consumer information. At best, it leads to an overestimation of the demand inducement, and in the worst case, we falsely accept the SID hypothesis. Using an unique measure of consumer information based on responses to survey questions about health competence, we estimate the demand for office visits and length of stay in hospitals within a hurdle model framework. Our contribution to the literature is the use of this novel measure of consumer information and the application of the Poisson hurdle model in this context. To our knowledge, we are the first to use this particular estimation strategy. We assume that a measure of consumer information which is in line with the demand inducement hypothesis does not alter the probability of visiting a physician and going to the hospital, respectively. However, if the SID hypothesis was true, the consumer information should affect the amount consumed, *ceteris paribus*. Our empirical results indicate that both the number of visits and the length of stay decrease with a higher level of consumer information. Hence, we find evidence in favor of the SID hypothesis.

The remainder of this paper is structured as follows. The next section presents a theoretical model of SID given a specific consumer and health care provider behaviour from which we obtain the main hypotheses. Section 3 describes the data and the empirical approach and the key findings are discussed in section 4. Finally, the last section contains some concluding remarks and deals with some limitations of the analysis.

## 2 Theoretical Framework

### 2.1 The Swiss Health Care System

The Swiss health care system is a mixture between competition enforcing elements and governmental regulations mainly on the federal level.<sup>1</sup> On the one hand, the basic health insurance is provided

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<sup>1</sup>An extensive summary on the Swiss health care system is provided by the European Observatory on Health Care Systems and the World Health Organization (WHO, 2000) in the Health Systems in Transition (HiT) series.

by private insurance companies. Although the health insurance providers are not allowed to make profits in the basic insurance, they can sell gainful supplementary insurance plans to their customers. In addition, general practitioners and specialists are generally self-employed and around 40% of the hospitals are private. Health care providers are paid on a fee-for-service (FFS) basis.<sup>2</sup> On the other hand, the basic health insurance is mandatory for all Swiss residents. Furthermore, the government determines the coverage of the basic insurance as well as the corresponding deductible and co-payment, approves the monthly premium and decides on the fees paid per unit of medical care. Finally, the health insurance providers are obliged to contract with every licensed health care provider.

While the basic insurance coverage is fixed, individuals can freely choose the health care provider<sup>3</sup> and have some choice with respect to their cost sharing. The selectable deductible ranges from CHF 300 to CHF 2500 for adults and from zero to CHF 600 for children. An increase in the deductible leads to a lower monthly premium. Additionally, the monthly premium differs across the three age groups children (0-18), young adults (18-25) and adults (above 25). Independent of the selected deductible, all adults have to pay a fixed co-payment of 10% up to the cumulative amount of CHF 700 (children: CHF 350) whenever the expenditures exceed the individual deductible. Hence, a patient has to bear a fraction of the cost if his health care expenditures amount to CHF 7300 - 9500 (children: CHF 3500 - 4100), while expenditures above this amount are fully paid by the insurance provider.

Some of the above mentioned features of the Swiss health care system are suspected to stimulate demand inducement. In his model, Dranove (1988) points out that supplier demand inducement increases in insurance coverage and decreases in the diagnostic skills of the patient. In addition, physicians paid on a FFS basis tend to induce demand while fixed salaries and HMOs remove the incentives for demand inducement. The findings of Birch (1988) on the market for dentistry in the United Kingdom corroborate this conclusion about FFS systems. Moreover, due to the obligation to contract, insurance providers have to reimburse health care expenditures without the possibility to

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<sup>2</sup>In 2012, the reimbursement system for hospitals changed, i.e. hospitals are now paid with lump compensation.

<sup>3</sup>Some insurance provider offer health plans where the individuals are bounded to a specific (group of) health care provider, e.g. an HMO, PPO, or family doctor. In practice, only 14.93 % of the Swiss residents did choose such a health plan in 2007. Notice that the insurance coverage is not altered by this choice and the selected health care provider can be changed easily.

control for unnecessary services and without the potential to sanction malpractice. Hence, the Swiss health care system and its features seem to be well-suited to test the SID hypothesis. Therefore, we use a simple model that captures these features adding differences (e.g. diagnostic skills) in individual information to derive some theoretical results. These results and hypotheses respectively can then be used to test the SID hypothesis.

## 2.2 Patient

As Grossmann (1972) recognizes, health is not an ordinary good and cannot be bought on a market. Consumers rather produce their own health level according to some inputs, e.g. medical care. We adopt this idea by specifying health, denoted  $h$ , as the output of a function  $g(\cdot)$  decreasing in the individual's health status  $\theta \in [0, 1] = [\text{death}, \text{perfect health}]$  and increasing in effective medical care denoted  $m_e$  which can be bought in the health care market. New to the SID literature is the introduction of (practical) medical know-how denoted  $\phi_j$  in the health production function. Medical know-how can be acquired by the consumers due to an occupation in the health care sector and might alter the demand for health care through several ways. Essentially, medical know-how is an input in the individual's health production. Given that an individual with a medical background obtains medical treatment, the treatment is then more effective since the individual itself can add something. For example, a nurse can change a bandage herself or a pharmacist knows whether a prescribed drug adversely interacts with another drug that she takes. In addition, individuals with a medical occupation could have another attitude towards medical care or health and it is possible that individuals working in the health care sector have access to informal care, e.g. due to 'professional courtesy' (see Bunker and Brown (1974)). While another attitude might increase the demand for health services, the other effects described clearly decrease the price of health. Depending on the income and substitution effect, the demand for medical care either increases or decreases. Finally, we assume that the physician density denoted  $\rho$  enters the individual's health production function to ensure that  $h = g(\rho = 0, \cdot) = 0$  even if  $\phi_j > 0$ .

Given the health production function  $g(\cdot)$ , we specify the utility of the representative patient as  $u_p(c_p, h)$ , where  $c_p$  is consumption and  $h$  is health. By assuming that  $\phi_j \sim iid$  with mean  $\phi$  and finite variance, the objective function of the representative agent can be written as

$$u_p = u(c_p) + h, \text{ where } h = g(\theta, m_e, \phi, \rho) \quad (2.1)$$

The additive objective function resembles the utility functions proposed by Farley (1986) and Dranove (1988). However, medical care is not a single input and does not directly yield utility in our specification. Thus, we can directly model how medical know-how affects the individuals health status and account for the special characteristics of health recognized by Grossmann (1972) at once. In addition, we discuss the budget constraint of the representative patient in the next paragraphs separately since supplier induced demand directly affects the budget constraint and is itself limited due to this financial constraint.

First, we introduce theoretical (medical) knowledge  $I_j \in [0, 1]$  which is used to judge the physician's advice and received treatment. Hence, it is not an input in the individual's health production. It can be acquired by reading books, watching TV, experience or professional medical training. Indeed, it is reasonable to assume that physicians have the highest possible value of  $I_j$ . Moreover, we believe that theoretical medical knowledge is the element called "information" in the whole SID literature. The representative patient has some average theoretical medical knowledge  $I \equiv E[I_j]$  with a corresponding potential induced medical care denoted  $m_i(I)$ . By definition, the marginal utility of one unit of induced demand has to be below the marginal utility of a unit of effective medical care. As a simplification it is therefore assumed that induced medical care does not enter the utility function directly. Finally, overall medical care can then be written as  $m = m_e + m_i(I)$ , i.e. adding induced medical care  $m_i(I)$  to the effective medical care  $m_e$ .

The overall price of medical care  $m$  is denoted  $\pi(p_m, p_t, \rho)$ , defined as a function of the payment of the physician per unit of medical care,  $p_m$ , the time and travelling costs of the representative patient,  $p_t$ , and the physician density  $\rho$ . Since the population and the area are given, an increase of the physician density leads to a shorter travelling distance and a decrease in waiting time. Hence, the overall price of medical care decreases in  $\rho$ . However, we assume that this effect diminishes as  $\rho$  gets larger due to the fact that travelling distance and waiting time are bounded at zero. Note that we abstract from time costs related to the actual consultation since the latter is assumed to be constant.



Furthermore, the representative patient has an insurance that bears  $(1 - \delta)$  of all medical expenditures  $\pi m$ . Hence,  $\delta \in [0, 1]$  corresponds to the co-payment of the patient. The premium for the insurance  $B$  is given by  $(1 - \delta)\pi m$  and the out of pocket payment equals  $\delta\pi m$ . Note that the representative agent does not take into account that the premium is affected by its own actions. The representative patient has income  $y$  and the price of consumption is normalized to one. Summarizing, the budget constraint which must be binding in any optimum is given by

$$y = c_p + \delta \cdot \pi \cdot m + B \quad (2.2)$$

Combining the objective function (2.1) of the representative agent with his budget constraint (2.2), one can obtain the Walrasian demand for health care given by

$$m_e^d = m(\theta, \delta, y, \pi, m_i(I), \phi) \quad (2.3)$$

Due to the assumptions stated above, the demand for effective medical care depends negatively on health status  $\theta$ , the co-payment rate  $\delta$ , the price  $\pi$ , and the induced demand  $m_i(I)$ . Further it depends positively on income  $y$  while the effect of  $\phi$  is not determined. Henceforth, we assume that the mentioned price effect of medical know-how leads to a reduction in the demand for effective health care. Note that induced demand affects demand through two channels. First, some fraction of the out-of-pocket payments is used to pay induced demand. Second, induced demand leads to a higher insurance premium. Hence, the budget of the representative agent is negatively affected by the overall inducement in the market. Therefore, induced demand is crowding out consumption as well.

## Physician

We specify the utility of the representative physician  $v_a$  as a convex and twice differentiable function increasing in consumption  $c_a$  and leisure  $(1 - l)$ :

$$v_a \equiv v(c_a, 1 - l) \quad (2.4)$$

Consequently, we assume that the representative physician is a utility maximizer and does not target a certain income level. However, the basic results will not be affected by this assumption. In addition, we assume that all physicians are self-employed and labor  $l$  is used as single input in their production function. Labor can be used to produce effective medical care or to induce demand. We assume that the physician prefers producing effective medical care. On the one hand, the physician could be altruistic and, therefore, inducing demand causes moral costs (see ?, ?). On the other hand, it might require a higher level of effort to convince the patient to buy services that are completely useless. Hence, this can be implemented by assuming the physician's productivity to be lower in the inducement process. These effects are captured by the parameter  $\eta \in (0, A]$ , where  $A$  denotes factor productivity. Although  $\eta$  could depend on the patient's utility, we assume a fixed value for simplicity. Assuming a linear production function, the physician's production can be written as

$$f(l) = sAl + (1 - s)(A - \eta)l \quad (2.5)$$

where  $s$  denotes the fraction of labor producing effective medical care. However,  $s$  cannot be chosen by the physician. It is determined by both the demand and supply for medical services, i.e. an excess supply of effective medical care implies  $s < 1$ . Hence,  $s$  depends directly on the choice of labor  $l$ , the demand for effective medical care,  $m_e^d$ , per physician, and indirectly on the productivity reduction parameter  $\eta$ .

Recall that the payment per unit of medical services provided by the physician is  $p_m$ . Combining this with equation (2.5) yields the physician's budget constraint

$$c = p_m \cdot f(l) = p_m \cdot (A - \eta + \eta s) \cdot l \quad (2.6)$$

The utility of the representative physician is maximized if and only if  $s = 1$ . Moreover, as long as  $\eta < A$  the physician induces demand for any  $s < 1$ . This implies that a physician does not induce demand if and only if he solely assigns weight to the patient's utility and not to his own wellbeing. Finally, we normalize the numbers of patients to one. Hence, the physician density equates the number of physicians in the market such that the supply of effective medical care and the supply

of desired induced demand equal

$$m_e^s = \rho s A l \text{ and } m_i^s = \rho(1 - s)(A - \eta)l \quad (2.7)$$

## Theoretical Results

Given the fairly simple behavior of patients and physicians described above, the model implies without inducement an optimal point, a suboptimal region with rationing, and an overoptimal region as shown in Figure 1.<sup>4</sup> The solid lines correspond to the demand of the representative agent in per physician terms and the supply per physician. Hence, the area below the solid lines equates to the total quantities. Note that the optimum is defined as the point where demand meets supply. This is an important point since the optimum from a welfare perspective is to the left of the crossing point in Figure 1 due to the present moral hazard. Even in the rationing case, supply can be too large from a welfare perspective, i.e. the physicians can benefit from the moral hazard of the patients (given  $\rho \in (\rho^{soc}, \rho^{opt})$ ). In addition, the dashed lines in Figure 1 correspond to the individuals with no medical know-how and with the maximal medical know-how, respectively. As assumed earlier, medical professionals have a smaller demand for medical care. Their optimal consumption is to the left of the optimal crossing point between the solid and the dashed line. Hence, even if the SID hypothesis was false, health professionals consume less medical care in this framework.

As Figure 1 demonstrates, without demand inducement the rationing in the overoptimal region takes place at the physician's level. However, assuming that demand inducement is possible and takes place, the situation changes as given in Figure 2. The solid lines show the consumed output of health care and the induced demand. The dashed line indicates the original situation of the representative patient from Figure 1 abstracting from the differences in medical know-how. If  $\rho$  exceeds  $\rho^{opt}$ , the physicians start to induce demand which increases steadily up to  $\rho^{sb}$ . At this point, the inducement potential is fully exploited by the physicians. In other words,  $m_i(I)$  is at a maximum level. Note that the full potential for demand inducement is fixed and bounded due to

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<sup>4</sup>The existence of an equilibrium, i.e. a crossing point, is not guaranteed without any further assumptions on the functional forms and parameter values. Basically, as  $\rho$  becomes large the demand per physician has to approach zero while the (possible) output per physician remains positive but finite. However, we assume that the functional forms and parameter values are such that the crossing point exists for  $\rho \in (0, 1)$ .

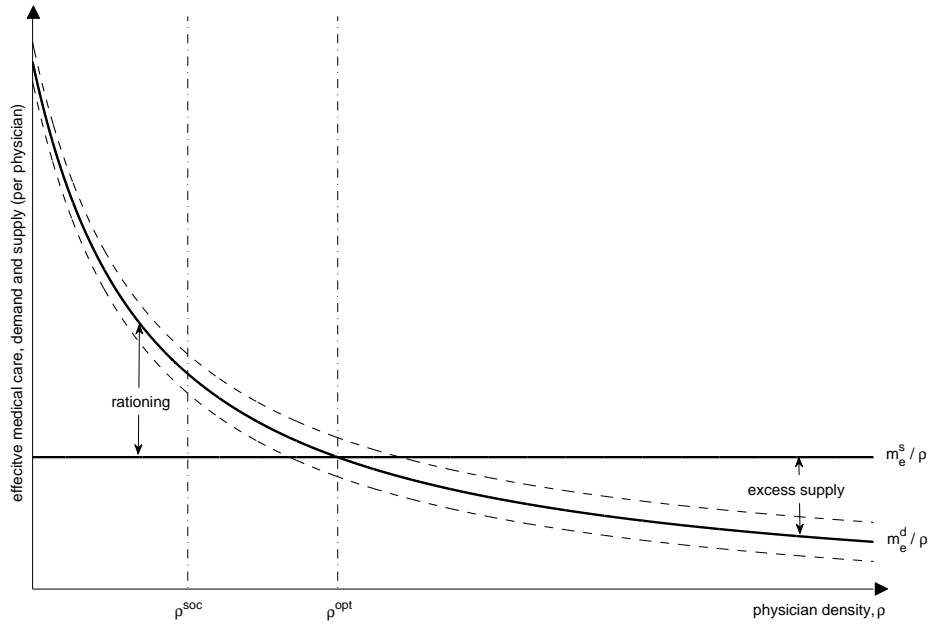


Figure 1: Demand and supply without demand inducement

the economic constraints of the patient.<sup>5</sup> Above this level, the demand for effective health care,  $m_e$ , and the induced demand,  $m_i$  is spread across all physicians. However, the demand inducement pushes the overall consumption of medical services,  $m = m_e + m_i(I)$ , above the dashed line, i.e. the demand which would have been realized with the fully informed patient with medical know-how  $E[\phi_j]$ .

Now we combine these two findings. For simplicity, we assume for the moment that both  $\phi$  and  $I$  can take the values zero and one only. Hence, there are four possible combinations for  $\phi$  and  $I$ . However, as mentioned the case  $\phi = 1$  and  $I = 0$  does not make any sense. Therefore, we compare only the three remaining combinations in Figure 3. The solid lines show the overall consumption of medical services by the patients with and without practical medical knowledge. Moreover, we assume in a first step that know-how and information is perfectly correlated. Hence, individuals with the combination no know-how but positive information do not exist and the dashed line in

<sup>5</sup>Given a patient has  $I = 0$  and  $\rho = \rho^{sb}$ , the physician would entirely extract the patients' income. One way to resolve this problem is to introduce ethic constraints (for example in Reinhardt (1985), Farley (1986)). However, the present framework offers two other solutions. First, the lower bound of  $I$  could be strictly positive, implying that the patients are not completely naive. Second, one can impose consumption constraints, e.g. a minimal consumption level. In the extreme case, the patient pays the premium and never visits the physician. Both possibilities are not implausible.

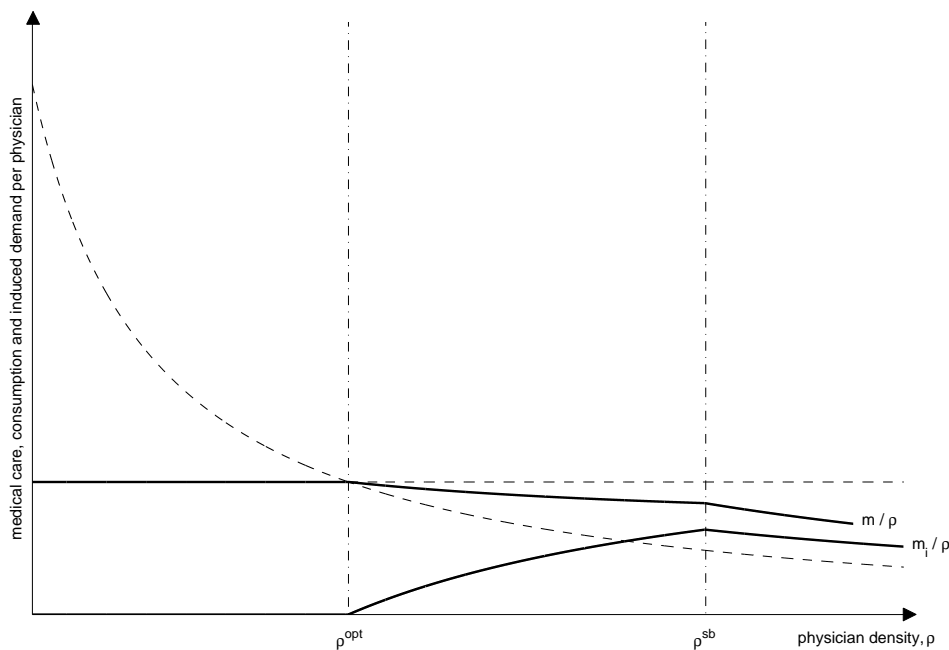


Figure 2: Demand and supply with demand inducement

Figure 3 is for theoretical purposes only. Hence, Figure 3 shows the worst case scenarios due to the perfect correlation assumption. Here, the difference in consumption of medical professionals and non-medical professionals equates to the sum of the know-how effect and the demand inducement effect.

In this setup, running a simple regression of medical care utilization on professional status would yield a coefficient that is too large. In fact, it can even be worse. Suppose physicians do not induce demand, then the dashed line is the realized consumption of medical services by the uninformed and unable patient. A regression would yield just the ability difference. However, the standard physician-patient hypothesis would tell us that this is SID. To summarize, if patients differ in at least two dimensions affecting health care utilization, using their professional status will prevent the econometrician from consistently estimating the effect. This conclusion remains valid even if we consider the family of health professionals, e.g. their spouses as in Bunker and Brown (1974) and Hay and Leahy (1982) or children as in Domenighetti et al. (1993), as these groups have easy access to informal medical treatments through their families.

However, it is not very reasonable to assume that medical know-how and theoretical medical

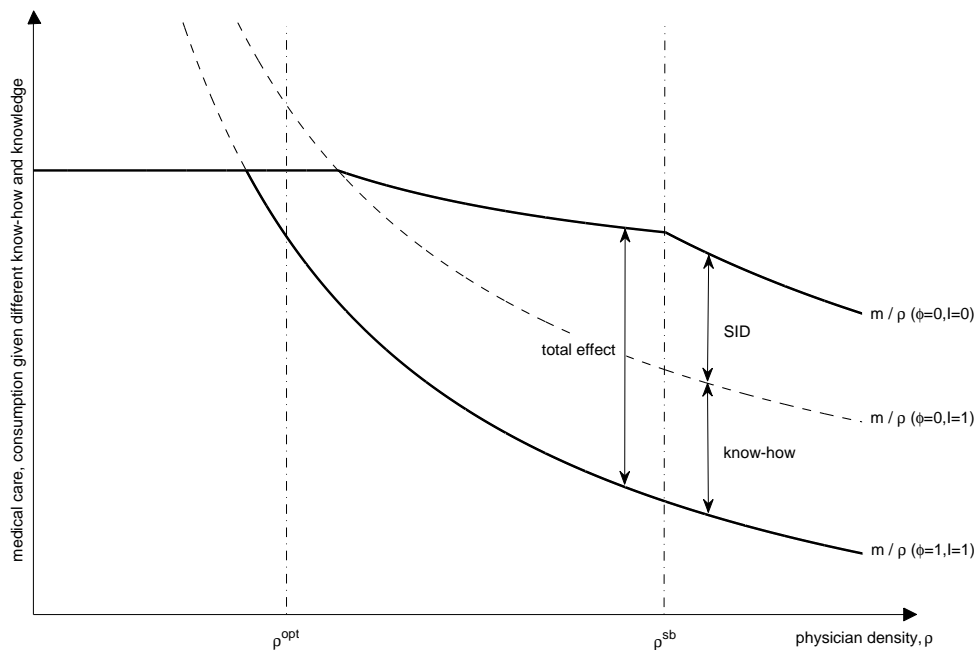


Figure 3: Worst case scenarios

knowledge are perfectly correlated. But the criticism mentioned above still remains valid as long as the latter cannot be measured. Contrary, if a measure for theoretical medical knowledge exists, it can be used to find evidence for the *existence* of demand inducement. One possible case is depicted in Figure 4 where the additional solid line corresponds to an individual with no medical know-how but some positive information level. Hence, it is sufficient for finding evidence of SID to have some individuals with some theoretical medical knowledge which do not work as health professionals, i.e.  $E[I|\phi = 0] > 0$ . However, Phelps (1986) asks whether we can ever know the *extent* of demand inducement. In the present framework, the answer to this question is clearly no. The individual with perfect information who is not a physician does not exist, since the maximum information is defined as the information level of the physician. Hence, there is no individual on the dashed line in Figure 4. In summary, using solely the profession leads, at best, to an overestimation and, at worst, to falsely accepting the demand inducement hypothesis. Therefore, we need an additional variable that measures theoretical medical knowledge to identify SID, but even with such a variable it is impossible to estimate the extent of demand inducement.

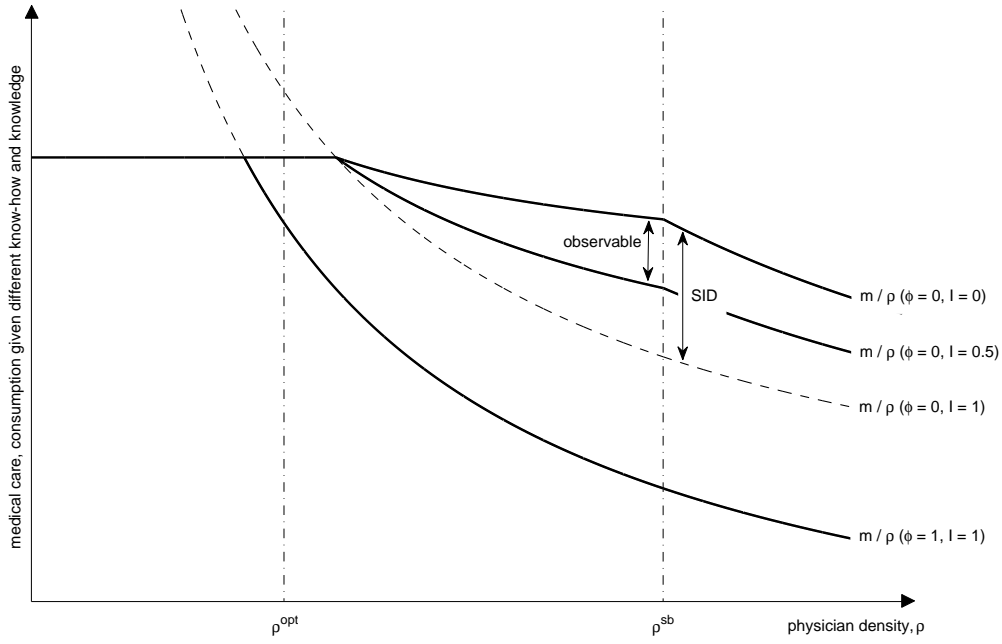


Figure 4: Possibility to identify supplier-induced demand

### Testable Hypothesis

According to the model, the total amount of consumed medical services in the the right of  $\rho^{opt}$  depends on both the behavior of patient  $j$  and the physicians, i.e.

$$m_j = m_{e,j} + m_{i,j}^s(I_j) = m_e(\theta, \delta, y, \pi, m_i^s(I_j), \phi_j) + \rho(1-s)(A-\eta)l \cdot b(I_j) \quad (2.8)$$

where the function  $b(I_j)$  determines how the physicians allocate induced demand among their patients.<sup>6</sup> According to the underlying theory about demand inducement,  $b(I_j)$  has to be strictly decreasing in  $I_j$ ,  $b(I_j = 1) = 0$ , and in addition we assume that  $b(E[I]) = 1$ . Hence, less informed patients receive more induced demand and consume more medical services ceteris paribus. By comparing patients with diverse medical knowledge and their consumption of medical services, e.g. measured by physician visits, we are able to find evidence for the SID hypothesis. Under the null, medical knowledge has no effect on consumption. If we can reject the null, a negative effect of medical knowledge on consumption provides evidence for the SID hypothesis. Obviously, we have

<sup>6</sup>We neglect in (2.8) the negative effect of total demand inducement in the market, i.e. the increased insurance premium, on the demand for effective medical care since all patients are affected equally. The same argument holds for positive effects of the overall know-how of the patients.

to control for the factors in (2.8) determining the demand for medical care, e.g. income and health status, as well as for other factors related to demand, health status and health behavior like age, gender, physical activity, and so on.

In addition, we are able to abstract in the theoretical model from the fact that some individuals do not have a positive consumption of medical services since we work with a representative patient. Moreover, we implicitly assume that medical care is continuous. However, medical care is consumed rather in discrete units, e.g. physician visits. In that case, the decision to visit the physician depends on the utility gained from the treatment and the resulting decrease in utility due to the consumption reduction. In addition, the decision for the first visit is made solely by the (potential) patient while follow-up visits are jointly determined by the patient and the physician. Therefore, we apply a two-part model. Since theoretical medical knowledge is used to judge the physician's behavior only, it should have no effect on the decision for the first visit. If we could reject this null hypothesis, our measure of medical knowledge would measure something that is not only useful for judging physician behavior. Therefore, we would fail in finding evidence for the SID hypothesis even if medical knowledge had a significantly negative effect on the consumed amount of medical services. In summary, we apply a two-part model where theoretical medical knowledge should have no effect on the decision to have a positive consumption but negatively affects the consumed amount given positive consumption. Otherwise, we are not able to find evidence for or against the SID hypothesis.

### **3 Empirical approach**

The data used in this paper is taken from the Swiss Health Survey conducted in 2007 by the Swiss Federal Statistical Office. The data is based on interview by phone and an additional online and paper-based form. A random sample of 18'760 individuals out of the Swiss resident population aged between 15 and 99 has been interviewed by phone. The data set from the phone-based interview includes detailed information about health status and insurance, health related behavior, utilization of medical services, and the socio-economic background on the individual level. Moreover, some data about the respondent's household structure is provided as well. The additional data from the paper-based part are primary an extension in terms of health status and utilization of specialized



medical services. Secondary, it adds data about the respondent's health expertise, labor situation, and addiction. However, only 79.36% of the interviewed individuals agreed to fill out the additional form. Since some variable of interest, especially the health expertise (see below), is included only in the reduced sample, the analysis in this paper is based only on 14'393 individuals.<sup>7</sup> Table 1 provides variable definitions and descriptive statistics of the explanatory variables.

The measure for the individual's health expertise is constructed using answers to five questions about their self-confidence related to health issues. Concretely, the respondents were asked to give a self-evaluation about their own abilities dealing with health care issues. In the first question, the respondent were asked about the importance of critically questioning given health information. The range of possible answers was from one (very important) to four (not important). In addition, the fifth possible answer was 'I cannot assess' implying that the respondent has not the ability to evaluate health information. The other four questions were related to knowledge about healthy behavior, consumption behavior in terms of buying and using over the counter drugs and food additives, patient behavior in terms of communication e.g. with a physician, and general knowledge about health issues. In all four questions, the range of possible answers was one (feel very certain) up to five (does not feel certain at all). We combined these five categorical variables to one dummy variable denoted *INFO* where 1 indicates that an individual answered all questions with at least 'important' or 'feel certain'. We expect that this is a good proxy for the individual's information level. Kenkel (1990) proceeds in a similar fashion using ten questions about symptoms associated with diabetes, heart disease, cancer and tuberculosis. While his information measure is quite objective but narrow due to the restriction on four diseases, our information measure is more subjective but broader. In addition, we do not sum up the answers since we have categorial variables. Using the information measure described above, the probability for physicians and dentists having a 1 equates 0.369 and is therefore 2.35 times larger than for non-health professionals with a probability around 0.156. Hence, health professionals have on average a higher information level than non-health professionals which is consistent with the theory. Due to the implications of the model and the arguments stated above, we expect *INFO* to have a statistically significant negative effect on the number of office visits but no effect on the probability to visit a physician.

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<sup>7</sup>We do not expect severe selection issues since the mean outcome in age, gender, physician visits and the health status based on symptoms are not significantly different.

According to the theoretical model, the second important variable is the individual's medical know-how. In the following analysis, medical know-how is measured by a dummy-variable denoted *MEDOCC* indicating the profession and occupation, respectively. *MEDOCC* takes the value one if an individual is working in the health care sector including physicians, dentists, oculists, pharmacists, and physiotherapists. Additionally, the physician density is of special interest. On the one hand, the well-known positive relationship between physician density and demand for medical care is one of the starting points of the whole SID literature (e.g. Evans (1974), Fuchs (1978), Reinhardt (1985), and Cromwell and Mitchell (1986)). There are at least two possible explanations for this positive correlation. First, physicians may induce more demand in areas with high competition. Second, physicians may settle down in areas with high demand. Even though the mentioned authors are aware of this endogeneity problem and applied two-stage least squares, Dranove and Wehner (1993) show that this empirical approach fails to identify SID. On the other hand and as mentioned before, more physicians in a certain area may lower the individual's cost of health care. In fact, according to Auster and Oaxaca (1981) it is almost impossible to identify SID using the physician density. However, all the described effects go in the same (positive) direction and may significantly alter the demand for health care. Hence, controlling for the physician density might be appropriate. The corresponding variable denoted *PDENS* is defined as number of physicians per thousand residents on a cantonal level. A similar argument can be stated for the density of hospital beds denoted *HDENS*. The data for the two density variables has been retrieved on a cantonal level from the Swiss Federal Statistical Office.

Although we are mainly interested in the effects of the mentioned variables on utilization given a positive observed demand, we follow the idea of Hay and Leahy (1982) and estimate a two-part model, i.e. a non-nested hurdle model using a Poisson regression approach (see Mullahy (1986)). Hence, we assume that the statistical processes governing individuals to visit a physician and their number of visits are clearly distinct and different. Since demand inducement is possible only if demand is positive, medical information should have a significant effect in the second stage but not in the first stage. Otherwise, the variable would measure something that alters the overall demand and, therefore, cannot be used to identify SID. Note that the variables of interest, the number of physician visits and length of stay, exhibit overdispersion meaning that the (conditional) variance

is larger than the (conditional) mean. This violates the assumption of the basic Poisson model such that a generalized specification should be applied. A common generalization is the negative binomial regression model (Cameron and Trivedi (1986), Winkelmann and Zimmermann (1995), Winkelmann (2008)) where the density is given by

$$f(y_j) = \Pr(Y_j = y_j) = \frac{\Gamma(\theta + y_j)}{\Gamma(\theta)\Gamma(1 + y_j)} \left(\frac{\theta}{\theta + \lambda_j}\right)^\theta \left(\frac{\lambda_j}{\theta + \lambda_j}\right)^{y_j} \quad \text{for } y_j = 0, 1, 2, \dots, N \quad (3.1)$$

with  $E[Y_j|x_j] \equiv \lambda_j = \exp(x_j'\beta)$ ,  $x_j$  is a vector containing the explanatory variables,  $\Gamma(\cdot)$  is the standard gamma function and  $\theta \equiv \frac{1}{\alpha}$ , where  $\alpha$  denotes the variance of the gamma distribution. Note that overdispersion may be due to unobserved heterogeneity in health care utilization. This can be taken into account by adding an individual error term to the random mean function for  $Y_j$ , i.e.  $\tilde{\lambda}_j = \exp(x_j'\beta) \cdot \exp(\varepsilon_j)$  given the underlying assumption that  $\exp(\varepsilon_j)$  follows a gamma distribution with mean one and variance  $\alpha$ . The negative binomial Poisson distribution can then be obtained by inserting  $\tilde{\lambda}_j$  in the standard Poisson distribution. Finally, the resulting distribution in (3.1) has conditional mean  $E[Y_j|x_j] = \lambda_j$  and variance  $Var[Y_j|x_j] = \lambda_j + \alpha\lambda_j^2$ . In the case of  $\alpha = 0$ , the negative binomial Poisson distribution collapses to the standard Poisson distribution. Since  $\alpha$  has to be estimated, one can test whether the negative binomial Poisson model is appropriate or not.

However, the restriction to strictly positive numbers implies a truncation. The density of the truncated negative binomial regression model is given by

$$f(y_j|y_j > 0) = \Pr(Y_j = y_j|y_j > 0) = \frac{f(y_j)}{1 - \left(\frac{\theta}{\theta + \lambda_j}\right)^\theta} \quad (3.2)$$

where  $f(y_j)$  corresponds to the density given by (3.1) and  $\Pr(Y_j = 0) = \left(\frac{\theta}{\theta + \lambda_j}\right)^\theta$ . Following Grootendorst (1995), we assume a sample with *iid* distributed observations (individuals), where  $j = 1 \dots n$  individuals have a positive utilization of medical services and the remaining  $j = n+1 \dots N$  individuals do not visit a physician. The likelihood of the entire sample is then given by

$$L = \prod_{j=1}^n \Pr(y_j > 0|x_j) \cdot f(y_j|y_j > 0, x_j) \times \prod_{j=n+1}^N \Pr(y_j = 0|x_j) \quad (3.3)$$

or, using the fact that the likelihood function factors into two multiplicative terms:

$$L_1 = \prod_{j=1}^n \Pr(y_j > 0|x_j) \times \prod_{j=n+1}^N \Pr(y_j = 0|x_j) \quad (3.4)$$

$$L_2 = \prod_{j=1}^n f(y_j|y_j > 0, x_j) \quad (3.5)$$

The first term depends solely on parameters in the hurdle component of the model, e.g. the binary choice visiting a physician. Contrary, the second term depends exclusively on parameters in the level component of the model, e.g. the number of visits given  $y_j > 0$ . Due to this separability, the binary probability model can be estimated separately from the truncated Poisson model without losing any information (see also Mullahy (1998)). Therefore, we estimate a logit model for the binary choice visiting a physician and a truncated Poisson model for the number of visits. The vector of explanatory variables,  $x_j$ , contains the variables mentioned above and some additional controls which are described in the next paragraph.

Two categories of variables are expected to alter significantly the demand for medical care. The first category consist of variables capturing the individual health status. These variables are coded such that a higher value indicates a lower health level. Moreover, the healthiest group of individuals is always the reference group. We included a self-assessed health status and some more objective measures such as a variable for the health status based on the symptoms and severity of ten different diseases. Moreover, we include dummy variables for chronic diseases, impairment, accident within the last year, and pregnancy during the last twelve months. Two additional dummies indicate whether the individual had a physical examination related to cancer or chronic diseases (at least one year ago). Finally, we include two variables for mental health status. A dummy variable indicating a depression and a variable for psychological distress ranging from zero (normal) to two (high). Since the reference group of all these variables consists of the healthiest respondents, we expect for most of these variables a positive effect on utilization.

The second category contains variables about the insurance and, therefore, the price of medical care. First, we include a variable with three categories for the deductible ranging from one (below CHF 1000) to three (above CHF 2000). We expect a negative effect on the utilization of medical services, since an increase in the deductible implies a higher co-payment of the individual. Second, we

include a dummy variable where one indicates a supplementary insurance that covers complementary medicine. The expected effect is positive, since the overall coverage increases and the price decreases. Note that the supplementary insurance for hospitalization widens the possibility to chose the hospital as well as the surgeon and the rooms in the (semi-)private ward are more luxurious. However, the coverage with respect to medical treatments is not extended. Hence, we use supplementary insurance for hospitalization as control but we do not expect a positive effect on utilization.

Table 1 presents additional controls used in the estimation of the hurdle component and the count component as well as some descriptive statistics. We include variables for age, age squared, gender, body mass index, education, migration status, labor market participation, income and the household structure including the number of children. Moreover, we control for health related behaviour, i.e. sports as well as consumption of tobacco, alcohol and illegal drugs. Additionally, controls for the attitude towards health, family doctor (FD) and HMO model, the locus of control, and informal assistance are used. Finally, we include variables to control for regional effects and differences in the degree of urbanisation.

Table 1: Variable definitions and descriptive statistics

Variable	Definition	Mean	Std. dev.
<i>INFO</i>	= 1 if the respondent belongs to the 10% best informed individuals	0.1886	
<i>MEDOCC</i>	= 1 if the respondent has a medical occupation, namely: physicians, dentists, oculists, pharmacists, and physiotherapists.	0.0410	
<i>PDENS</i>	number of physicians with practice per 1000 residents (by canton)	2.0018	0.5424
<i>HDENS</i>	number of hospital beds per 1000 residents (by canton)	3.2349	0.8042
<i>SUBHLTH</i>	self-reported health status: coded 1 = very good, 2 = good, 3 = average, 4 = poor	1.8816	0.5316
<i>OBJHLTH</i>	symptom-based health status: coded 1 = very good, 2 = good, 3 = average, 4 = poor. Diseases: pain in the back, adynamia, abdominal pain, looseness or costiveness, sleep disorder, headache, heart palpitation or extrasystole, pain or pressure in the chest, joint pain or pain in the limbs, and pain in the hands	1.1209	0.9597
<i>CHRDIS</i>	= 1 if the respondent was under medical treatment due to at least one chronic disease, including migraine, asthma, diabetes, arthrosis, stomach ulcer, osteoporosis, chronic bronchitis, high blood pressure, heart attack, apoplexia, renal disease, cancer, allergy, and depression	0.5258	
<i>ACCID</i>	= 1 if the respondent had an accident at work, at home, road accident, and/or sporting accident	0.1114	
<i>PREGN</i>	= 1 if the respondent was pregnant within the last 12 months	0.0080	
<i>CANPREV</i>	= 1 if the respondent had a medical examination related to cancer prevention at least one year ago.	0.3533	
<i>DIAGN</i>	= 1 if the respondent received the diagnosis: high blood pressure, high cholesterol level, and/or diabetes	0.2798	
<i>MAJDEP</i>	= 1 if the respondent suffers from clinical depression	0.0450	
<i>DETPSY</i>	psychological distress of the respondent: coded 1 = low, 2 = medium, 3 = high	1.1704	0.4462
<i>DEDUCT</i>	insurance deductible: coded 1 = below CHF 1000, 2 = CHF 1000 - 2000, 3 = above CHF 2000	1.6134	0.7570
<i>ADDINS</i>	= 1 if the respondent has an additional insurance for alternative medicine	0.5700	
<i>HMOFD</i>	= 1 if the respondent has a health plan with a gatekeeper (e.g. HMO, family doctor)	0.1385	

Table 1: Variable definitions and descriptive statistics (cont'd)

Variable	Definition	Mean	Std. dev.
<i>SUPPINS</i>	= 1 if the respondent has a supplementary insurance for hospitalization	0.7288	
<i>AGE</i>	age of the respondent (in years)	49.142	15.563
<i>AGE2</i>	age of the respondent squared	2657.1	1611.4
<i>GENDER</i>	= 1 if the respondent is female	0.5197	
<i>BMI</i>	body mass index = weight in kilos divided by height in meters squared	24.393	3.8823
<i>EDUC3</i>	education level: coded 1 = mandatory school, 2 = secondary education, 3 = tertiary education	2.2560	0.5906
<i>MIGR</i>	= 1 if the respondent has a migration background	0.2463	
<i>EMPL</i>	gainfully employed: coded 1 = fully employed, 2 = part-time employed, 3 = non-working	1.8756	0.8419
<i>INCOME</i>	monthly income of the entire household: coded 1 = below CHF 4500, 2 = CHF 4500 - 5999, 3 = CHF 6000 - 8999, 4 = CHF 9000 and more	2.6679	1.1040
<i>COUPLE</i>	= 1 if the respondent is not single	0.6762	
<i>NBKIDS</i>	number of children in the household	0.4829	0.8908
<i>MOUVPHY</i>	frequency of physical activity: coded 0 = never, 1 = once or twice a week, 2 = three times or more	1.2731	0.6736
<i>SMOKE</i>	= 1 if the respondent is a smoker	0.2649	
<i>ALCO</i>	= 1 if the respondent drinks alcohol	0.8871	
<i>DRUG</i>	= 1 if the respondent abused (illegal) drugs during the past two years	0.0356	
<i>HLTHATT</i>	= 1 if the respondent answered that health/healthy behavior is important for her lifestyle	0.8933	
<i>MASTERY</i>	mastery level of the respondent based on 3 questionnaire items: coded 1 = weak control, 2 = average control, 3 = strong control	2.2018	0.7408
<i>IHELP</i>	= 1 if the respondent received informal/support help given daily difficulties	0.0775	
<i>MSREG14</i>	degree of urbanisation, respectively (fourteen categories)	6.2299	3.7650

## 4 Results

Table 2 reports the main results of the logit estimation for the hurdle part given by the likelihood in (3.4) and estimates obtained from the truncated negative binomial Poisson model for the count part given by the likelihood in (3.5).<sup>8</sup> The estimations for the office visits (physicians) are shown in columns (1) and (2) and for the length of stay (hospitals) in columns (3) and (4).<sup>9</sup> Recall that we are only interested in the sign of the effects since we are not able to estimate the extent of the demand inducement. In both models of the count component, the *INFO* coefficient is significantly negative. Moreover, the estimated coefficients are not significantly different from zero in both estimations of the hurdle component. Hence, the information does not alter the overall demand due to differences in attitude or skill, *ceteris paribus*. But in case of positive health service utilization, it seems to reduce the number of office visits as well as the length of a hospital stay. Therefore, we conclude that there is evidence for the SID hypothesis.

Contrary to the findings of Bunker and Brown (1974) and Hay and Leahy (1982), the coefficient of *MEDOCC* is negative and significant on the 1% level in both the hurdle equation and count equation for office visits. This is in the line with our argument that being a health professional alters overall demand. In addition, the know-how thesis is supported by a comparison of the *MEDOCC* coefficients and their significance, respectively, in the hurdle part of the office visits and length of stay estimation. In the latter, the coefficient is negative but insignificant while it is significantly negative in the former. In fact, in many circumstances it is reasonable to assume that even medical professionals need external help, e.g. for surgery, and medical treatments that necessitate a hospital stay are generally more difficult than ambulatory care. Hence, it makes intuitively sense that we cannot reject the null that *MEDOCC* has no effect on the probability to go to the hospital on a conventional level of significance (i.e. 5%). However, medical professionals do have a shorter stay on average. Doing the surgery on their own is not possible, but changing the bandage or checking for complications like infections afterwards can be done.

As predicted, the density coefficient in the office visit hurdle component has a positive effect

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<sup>8</sup>Note that the estimated  $\alpha$  was 1.5456 with a standard error of 0.1479. Hence, the choice of the negative binomial Poisson model compared to the standard Poisson model is appropriate.

<sup>9</sup>Pregnant women and individuals with poor subjective health status were excluded from the logit estimation of the hurdle component for office visits since pregnancy and poor subjective health perfectly predicts the office visit.



on utilization. In the hurdle equation, it probably captures an availability effect since it is hard to imagine that physicians can influence the decision to visit them before they are contacted. Note that physicians in Switzerland do not advertise their own services in general. Moreover, the coefficient in the count component is not statistically significant. Contrary, it is reasonable that the availability effect does not exist for hospitals, since travelling costs can be neglected in case of hospitalization. In addition, we do not conclude that the significantly positive effect (1% level) in the count component indicates SID, since the location choice of the hospital is probably endogenous.

The three main results with respect to the SID hypothesis as well as the results stated below are robust against several changes in the model specification and estimation method. First, we estimate the count part of the hurdle model with ordinary least squares and Tobit. In addition, we estimate the zero-truncated Poisson model without taking the overdispersion into account. Second, we reduce the number of controls from 32 to 11 and estimate the negative-binomial Poisson model again. Additionally, we estimate the same model with the full set of controls for the subsample of non-health professionals. The corresponding estimates are shown in Table 4, 5, and 6 in the appendix. They are comparable to our main results in terms of sign and significance. Finally, we tested several specification of the *INFO* variable in terms of considered questionnaire answers (out of five) and the threshold level. Regarding the sign and the significance of the effect, the results are not notably altered by excluding one variable or by changing the threshold (e.g. to 'very certain') of some variables. In summary, we conclude that our results are robust against changes in the model specification, estimation method, and the construction of the *INFO* variable.

As expected, better health leads to less utilization, especially in the office visit model. Moreover, the magnitude of the effect increases when health status is further decreased. Note that the other health measures tend to increase the utilization of health care services as well, thus supporting our empirical approach. One exception is *CANPREV*, the dummy variable indicating a physical examination related to cancer prevention. However, most of these examinations are done periodically (every 2 years or more). Hence, an examination last year implies that the next examination is earliest the next year. Finally, variables measuring the co-payment, overall coverage, and income tend to have the expected sign.

While most of the variables used exhibit expected results, our estimation method and information

proxy have some drawbacks. First, information might be endogenous and, therefore, would have no causal interpretation. Second, due to the construction and the underlying questions in the questionnaire, *INFO* might be a bad proxy for consumer information. In addition, the outcome variables are rather raw measures for the utilization of medical services. Third, we cannot control for the length of a visit, its quality and the effect on the individual's health. And finally, misreporting might be an issue.

Regarding the estimation procedure, there are two critical issues. First, by applying a two-part model we implicitly treat the whole year as one illness episode. In fact, we ignore the possibility that an individual decides two or more times to visit the physician once (per decision). However, in the length of stay estimations we only use observations with exactly one hospitalization during the last year. Since the results of the two count component estimations are similar, especially with respect to the *INFO* coefficient, this might be a rather small limitation of our estimation method. Second, in some estimations the sample size is reduced to 7706 observations due to missing data. In particular, unreported income and deductible accounts for nearly two thirds of the missing data. In addition, questions on additional insurances, chronic disease and accident were partially unanswered. However, we do not find any systematic differences in the dependent variables conditional on the missing values. Moreover, the estimates with the reduced set of controls using up to 10167 observations are comparable to our main results. We therefore conclude that sample selection is not an issue. In summary, our study exhibits some minor drawbacks. Nevertheless, the main criticism of the physician-patient approach remains valid and our empirical findings support this view.

Table 2: Results

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
<i>INFO</i>	-0.1068 (0.1107)	-0.1738 (0.0612)**	-0.1577 (0.1245)	-0.2429 (0.0959)*
<i>MEDOCC</i>	-0.6364 (0.1823)**	-0.3491 (0.1036)**	-0.2851 (0.2665)	-0.4374 (0.1866)*
<i>PDENS</i>	0.3380 (0.1209)**	0.0250 (0.0611)		
<i>HDENS</i>			0.0337 (0.0598)	0.1883 (0.0526)**

Table 2: Results (cont'd)

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
<i>SUBHLTH</i>				
good	0.1795 (0.0983)	0.2782 (0.0757)**	0.2568 (0.1364)	0.0883 (0.1226)
fair	1.0534 (0.2881)**	0.7951 (0.1171)**	0.6974 (0.2040)**	0.3102 (0.1539)*
poor		1.4974 (0.1940)**	1.8167 (0.2880)**	0.4937 (0.2167)*
<i>OBJHLTH</i>				
good	0.2748 (0.0969)**	0.2336 (0.0760)**	0.2269 (0.1324)	0.3517 (0.1065)**
fair	0.5227 (0.1247)**	0.3324 (0.0797)**	0.4294 (0.1540)**	0.3003 (0.1184)*
poor	1.0205 (0.2370)**	0.4290 (0.0953)**	0.1971 (0.2061)	0.4406 (0.1415)**
<i>CHRDIS</i>	0.8241 (0.0991)**	0.4794 (0.0635)**	0.3675 (0.1138)**	-0.0285 (0.0867)
<i>ACCID</i>	1.3290 (0.1957)**	0.4320 (0.0715)**	0.8532 (0.1278)**	-0.0665 (0.1102)
<i>PREGN</i>		0.6416 (0.1207)**	0.5714 (0.4392)	-0.3002 (0.2900)
<i>CANPREV</i>	-1.0261 (0.0867)**	-0.1252 (0.0603)*	-0.1727 (0.1082)	0.0198 (0.0861)
<i>DIAGN</i>	0.3358 (0.1075)**	0.1067 (0.0592)	-0.0412 (0.1118)	0.1384 (0.0931)
<i>MAJDEP</i>	1.1648 (0.2579)**	0.5525 (0.1273)**	0.2554 (0.2296)	0.3929 (0.1627)**
<i>DEDUCT</i>				
1000 - 2000	-0.4059 (0.1046)**	-0.2760 (0.0619)**	-0.1257 (0.1269)	0.1099 (0.1269)
> 2000	-0.7162 (0.1166)**	-0.2907 (0.0891)**	-0.1087 (0.1674)	-0.0385 (0.1190)

Table 2: Results (cont'd)

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay

\*  $p \leq 0.05$ , \*\*  $p \leq 0.01$

Estimation of a truncated negative-binomial Poisson hurdle model for office visits ( $N = 7706$  and  $N = 6392$  non-zero utilisation) and hospitalization ( $N = 7804$  and  $N = 606$ ) using data from the Swiss Health Survey 2007. Only main variables are shown in this table; the full table showing all controls can be found in the appendix.

## 5 Conclusion

The underlying question in the literature about SID is whether health care providers exploit their informational advantage for financial gains. Since the possibility to induce depends heavily on the information gap between provider and patient, one promising way to test the SID hypothesis is the comparison of well and badly informed patients. While the basic idea seems straightforward, finding an acceptable measure for information can be difficult. As we have argued, medical profession appears to be an inappropriate measure since working in the health care sector probably alters the utilization of medical services through other ways than just the resistance against demand inducement. As shown in a simple model, the professional or occupational status can therefore not be used to identify SID. Nevertheless, with an information measure that captures only medical knowledge which is used by the patient to judge the behaviour of the health care provider, the information gap approach can still be fruitful.

With respect to the broad discussion of the SID hypothesis during the last 40 years, our analysis yields two interesting results. First, medical professionals have a smaller demand, *ceteris paribus*. In particular, for standard treatments they have a lower probability of using medical services and use less of these services, implying that their overall demand is smaller. Therefore, we conclude that the theoretical results are accurate. Second, less informed people tend to have a higher utilization of medical services, which supports the demand inducement hypothesis. Moreover, the fact that information measured this way does not alter the probability of using medical services supports this view. Summarizing, medical occupation cannot be used to test for SID but it is still possible to

identify it with an alternative measure.

Our results have some important policy implications. First, an increase of the average information level of the whole population could lead to a lower utilization of health care services and help to reduce related expenditures. Second, it is possible to adapt the health care system such that the incentives to induce demand are dampened. This could, for example, be achieved by changing the reimbursement system, since the current FFS system is suspected to facilitate demand inducement. Furthermore, the obligation to contract between insurer and health care provider could be relaxed.

There are some limitations to the approach taken in this paper. In particular, office visits and length of stay are both rather raw measures of health care utilization and our information proxy could measure somehow the communication skills of the patient. If she can express herself with more accuracy, the physician might give her a treatment that is more appropriate and fewer follow-up visits. In addition, we do not distinguish between follow-up consultations and several independent consultations due to the Poisson approach. These issues might be resolved by using more comprehensive data on utilization and consumer information. Nevertheless, our findings suggest that consumer information plays an important role for the utilization of health care services. Further research in this area will help to disentangle the relationship between patients and health care providers and thus help to improve health care systems.

## A Full Table of Results

Table 3: Full Table of Results with all Controls

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
<i>INFO</i>	-0.1068 (0.1107)	-0.1738 (0.0612)**	-0.1577 (0.1245)	-0.2429 (0.0959)*
<i>MEDOCC</i>	-0.6364 (0.1823)**	-0.3491 (0.1036)**	-0.2851 (0.2665)	-0.4374 (0.1866)*
<i>PDENS</i>	0.3380 (0.1209)**	0.0250 (0.0611)		
<i>HDENS</i>			0.0337 (0.0598)	0.1883 (0.0526)**

Table 3: Full Table of Results with all Controls (cont'd)

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
<i>SUBHLTH</i>				
good	0.1795 (0.0983)	0.2782 (0.0757)**	0.2568 (0.1364)	0.0883 (0.1226)
fair	1.0534 (0.2881)**	0.7951 (0.1171)**	0.6974 (0.2040)**	0.3102 (0.1539)*
poor		1.4974 (0.1940)**	1.8167 (0.2880)**	0.4937 (0.2167)*
<i>OBJHLTH</i>				
good	0.2748 (0.0969)**	0.2336 (0.0760)**	0.2269 (0.1324)	0.3517 (0.1065)**
fair	0.5227 (0.1247)**	0.3324 (0.0797)**	0.4294 (0.1540)**	0.3003 (0.1184)*
poor	1.0205 (0.2370)**	0.4290 (0.0953)**	0.1971 (0.2061)	0.4406 (0.1415)**
<i>CHRDIS</i>				
	0.8241 (0.0991)**	0.4794 (0.0635)**	0.3675 (0.1138)**	-0.0285 (0.0867)
<i>ACCID</i>				
	1.3290 (0.1957)**	0.4320 (0.0715)**	0.8532 (0.1278)**	-0.0665 (0.1102)
<i>PREGN</i>				
		0.6416 (0.1207)**	0.5714 (0.4392)	-0.3002 (0.2900)
<i>CANPREV</i>				
	-1.0261 (0.0867)**	-0.1252 (0.0603)*	-0.1727 (0.1082)	0.0198 (0.0861)
<i>DIAGN</i>				
	0.3358 (0.1075)**	0.1067 (0.0592)	-0.0412 (0.1118)	0.1384 (0.0931)
<i>MAJDEP</i>				
	1.1648 (0.2579)**	0.5525 (0.1273)**	0.2554 (0.2296)	0.3929 (0.1627)**
<i>DETPSY</i>				
	-0.0301 (0.1290)	0.0374 (0.0524)	-0.0524 (0.1062)	-0.0031 (0.0774)
<i>DEDUCT</i>				
1000 - 2000	-0.4059 (0.1046)**	-0.2760 (0.0619)**	-0.1257 (0.1269)	0.1099 (0.1269)
> 2000	-0.7162	-0.2907	-0.1087	-0.0385

Table 3: Full Table of Results with all Controls (cont'd)

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
	(0.1166)**	(0.0891)**	(0.1674)	(0.1190)
<i>ADDINS</i>	0.1231	0.2633	0.1954	0.0649
	(0.0879)	(0.0545)**	(0.1021)	(0.0829)
<i>HMOFD</i>	0.0855	0.0695	-0.1507	-0.0398
	(0.1106)	(0.0635)	(0.1434)	(0.1272)
<i>SUPPINS</i>	0.0961	-0.0866	0.1822	0.1255
	(0.0979)	(0.0631)	(0.1119)	(0.0907)
<i>AGE</i>	-0.0810	-0.0176	-0.0323	-0.0054
	(0.0204)**	(0.0099)	(0.0184)	(0.0152)
<i>AGE2</i>	0.0009	0.0001	0.0003	0.0000
	(0.0002)**	(0.0001)	(0.0002)	(0.0001)
<i>GENDER</i>	0.9165	0.0226	-0.0571	-0.2332
	(0.1061)**	(0.0641)	(0.1161)	(0.1013)*
<i>BMI</i>	0.0098	0.0102	0.0345	0.0123
	(0.0124)	(0.0061)	(0.0129)**	(0.0083)
<i>EDUC3</i>				
secondary	-0.0869	0.0232	0.2344	-0.2268
	(0.1843)	(0.1046)	(0.1882)	(0.1428)
tertiary	0.1286	0.0440	0.2834	-0.0412
	(0.1976)	(0.1125)	(0.2116)	(0.1643)
<i>MIGR</i>	-0.0345	-0.0854	0.0053	-0.0530
	(0.1011)	(0.0569)	(0.1211)	(0.0939)
<i>EMPL</i>				
part-time	0.4333	0.2719	0.5095	-0.0099
	(0.1163)**	(0.0699)**	(0.1882)**	(0.1251)
non-working	0.2284	0.4119	0.2834	0.1486
	(0.1519)	(0.0904)**	(0.1555)**	(0.1201)
<i>INCOME</i>				
CHF 4500 - 5999	0.3335	0.0058	0.0213	-0.0566
	(0.1403)*	(0.0857)	(0.1562)	(0.1264)
CHF 6000 - 8999	0.4510	0.0321	-0.0594	0.0377
	(0.1366)**	(0.0835)	(0.1548)	(0.1203)

Table 3: Full Table of Results with all Controls (cont'd)

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
>= CHF 9000	0.7786 (0.1461)**	0.1257 (0.0935)	-0.0797 (0.1693)	0.1096 (0.1348)
<i>COUPLE</i>	-0.1368 (0.1096)	-0.0800 (0.0689)	0.2464 (0.1338)	-0.1854 (0.1103)
<i>NBKIDS</i>	-0.01939 (0.0483)	-0.0172 (0.0300)	0.1066 (0.0561)	0.0008 (0.0547)
<i>MOUVPHY</i>				
once/twice p. week	0.2951 (0.1596)*	-0.1597 (0.0760)*	-0.1949 (0.1604)	-0.1704 (0.1024)
three times or more	0.1048 (0.1538)	-0.1410 (0.0774)	0.0092 (0.1588)	-0.2596 (0.1152)*
<i>SMOKE</i>	0.0005 (0.0998)	0.0288 (0.0618)	0.2412 (0.1207)*	-0.0518 (0.0892)
<i>ALCO</i>	-0.1155 (0.1515)	-0.1345 (0.0835)	-0.0719 (0.1580)	-0.0371 (0.0889)
<i>DRUG</i>	-0.0339 (0.2231)	0.1439 (0.1256)	0.2029 (0.2812)	0.0372 (0.3755)
<i>HLTHATT</i>	0.5034 (0.1367)**	0.2885 (0.0811)**	0.1077 (0.1701)	0.1139 (0.1598)
<i>MASTERY</i>				
average	0.1555 (0.1299)	-0.0935 (0.0705)	0.0697 (0.1317)	0.1874 (0.1128)
strong	0.2842 (0.1314)*	-0.0287 (0.0799)	0.3082 (0.1422)*	0.2229 (0.1105)*
<i>IHELP</i>	-0.0071 (0.2048)	0.1207 (0.0818)	0.0984 (0.1718)	-0.1606 (0.1188)
<i>MSREG14</i>				
2	0.5881 (0.1970)**	0.1496 (0.1301)	-0.0731 (0.1922)	0.3567 (0.1937)
3	0.2329 (0.2146)	0.0420 (0.1270)	-0.0550 (0.2294)	0.3645 (0.1521)*
4	0.4872	-0.1123	-0.3133	0.1133



Table 3: Full Table of Results with all Controls (cont'd)

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
	(0.1974)*	(0.1171)	(0.2316)	(0.1482)
5	0.1048	-0.0959	-0.2492	0.3295
	(0.2099)	(0.1205)	(0.2122)	(0.2142)
6	0.2091	-0.1547	-0.3027	0.1566
	(0.2202)	(0.1212)	(0.2028)	(0.1449)
7	0.1139	0.0982	0.0776	0.1124
	(0.2106)	(0.1226)	(0.1932)	(0.1986)
8	0.4127	-0.0215	-0.2462	0.3372
	(0.1800)**	(0.1268)	(0.1845)	(0.1556)*
9	0.1578	0.0051	-0.1147	0.6094
	(0.2000)	(0.1294)	(0.2150)	(0.1591)**
10	0.4454	-0.1369	-0.0794	-0.1251
	(0.2497)	(0.1412)	(0.2757)	(0.1538)
11	-0.0877	0.0352	-0.1073	0.0642
	(0.2190)	(0.1380)	(0.2412)	(0.1668)
12	0.5533	-0.0737	0.5272	0.4210
	(0.2713)*	(0.1414)	(0.2963)	(0.2513)
13	0.1561	0.1333	0.2964	-0.0954
	(0.3618)	(0.1988)	(0.3979)	(0.2148)
14	0.4858	-0.0743	-0.3656	-0.4349
	(0.3334)	(0.1570)	(0.3507)	(0.2541)
cons	-0.0169	0.2001	-4.1132	0.5821
	(0.7331)	(0.3995)	(0.6358)**	(0.6037)

\*  $p \leq 0.05$ , \*\*  $p \leq 0.01$

Full table of results with all controls in the estimation of a truncated negative-binomial Poisson hurdle model for office visits ( $N = 7516$ ) and hospitalization ( $N = 7804$ ); main results are shown in Table 2.

## B Robustness

Table 4: Full Table of Results with reduced Controls

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
<i>INFO</i>	-0.0298 (0.0985)	-0.1278 (0.0578)*	-0.0740 (0.1112)	-0.2336 (0.0897)**
<i>MEDOCC</i>	-0.4047 (0.1656)*	-0.3001 (0.1042)**	-0.1783 (0.2277)	-0.5542 (0.1546)**
<i>PDENS</i>	0.2414 (0.0766)**	0.0657 (0.0377)		
<i>HDENS</i>			0.0916 (0.0462)*	0.1568 (0.0552)**
<i>SUBHLTH</i>				
good	0.1089 (0.0858)	0.3248 (0.0715)**	0.2565 (0.1217)*	0.1404 (0.1500)
fair	1.0037 (0.2317)**	0.8884 (0.1096)**	0.8396 (0.1672)**	0.3781 (0.1799)*
poor	5.6164 (1.0182)**	1.6143 (0.1546)**	1.8683 (0.2436)**	0.5728 (0.2317)**
<i>OBJHLTH</i>				
good	0.2950 (0.0869)**	0.2178 (0.0725)**	0.2172 (0.1196)	0.1867 (0.1253)
fair	0.5862 (0.1042)**	0.3287 (0.0730)**	0.3693 (0.1317)**	0.1930 (0.1372)
poor	0.9862 (0.1924)**	0.4627 (0.0856)**	0.2107 (0.1667)	0.1405 (0.1725)
<i>CHRDIS</i>	0.8231 (0.0857)**	0.4813 (0.0577)**	0.4440 (0.0992)**	0.1429 (0.0969)
<i>ACCID</i>	1.2957 (0.1784)**	0.4378 (0.0650)**	0.8053 (0.1092)**	-0.0857 (0.1154)
<i>PREGN</i>		0.8515 (0.1002)**	0.6581 (0.3854)	-0.5748 (0.1773)**
<i>MAJDEP</i>	0.8353 (0.2405)**	0.6855 (0.1088)**	0.0019 (0.1872)	0.4879 (0.2005)*
<i>DEDUCT</i>				

Table 4: Full Table of Results with reduced Controls (cont'd)

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
1000 - 2000	-0.4532 (0.0884)**	-0.2800 (0.0604)**	-0.3520 (0.1084)**	0.0560 (0.1341)
> 2000	-0.7444 (0.1058)**	-0.3137 (0.0811)**	-0.3695 (0.1430)**	-0.1765 (0.1298)
<i>ADDINS</i>	0.2237 (0.0760)**	0.2074 (0.0506)**	0.2247 (0.0889)*	-0.0916 (0.1018)
<i>HLTHATT</i>	0.5349 (0.1134)**	0.2012 (0.0765)**	0.1173 (0.1406)	0.0204 (0.2183)
cons	-0.5466 (0.2222)*	-0.4533 (0.1490)**	-3.3873 (0.2426)**	0.9797 (0.3480)**

\*  $p \leq 0.05$ , \*\*  $p \leq 0.01$

Estimation of a truncated negative-binomial Poisson hurdle model for office visits (total  $N = 9809$  and  $N = 7972$  given positive utilization) and for hospitalization ( $N = 10167$  and  $762$ ) using data from the Swiss Health Survey 2007 but with a reduced set of controls.

Table 5: Count Component estimated by OLS, Tobit and Poisson

Variable	Physician: Office Visits			Hospitalization: Length of Stay		
	OLS	Tobit	Poisson	OLS	Tobit	Poisson
<i>INFO</i>	-0.4672 (0.2401)*	-0.4672 (0.2390)*	-0.1100 (0.0556)**	-1.6006 (0.7839)**	-1.6006 (0.7461)**	-0.2207 (0.1005)**
<i>MEDOCC</i>	-1.0428 (0.2829)***	-1.0428 (0.2816)***	-0.2796 (0.0796)***	-2.6536 (1.2949)**	-2.6536 (1.2324)**	-0.4726 (0.2206)**
<i>PDENS</i>	0.0818 (0.2889)	0.0818 (0.2876)	0.0101 (0.0579)			
<i>HDENS</i>				1.8562 (0.7540)**	1.8562 (0.7176)***	0.2088 (0.0565)***

\*  $p \leq 0.10$ , \*\*  $p \leq 0.05$ , \*\*\*  $p \leq 0.01$

Estimations of the count component using OLS, Tobit and zero-truncated Poisson with the same full set of controls as in Table 3. The number of observations equates  $N = 6392$  for the office visits and  $N = 606$  for the length of stay, i.e. we use the same observations as for our main results.

Table 6: Subsample estimates using the neg-bin Poisson hurdle model

Variable	Office Visits		Hospitalization	
	Hurdle: Physician	Number of Visits	Hurdle: Hospital	Length of Stay
<i>INFO</i>	-0.1104 (0.1156)	-0.1562 (0.0638)*	-0.1482 (0.1278)	-0.2360 (0.0994)*
<i>PDENS</i>	0.3381 (0.1255)**	0.0238 (0.0636)		
<i>HDENS</i>			0.0272 (0.0614)	0.1900 (0.0533)**

\*  $p \leq 0.05$ , \*\*  $p \leq 0.01$

Estimation of a truncated negative-binomial Poisson hurdle model for office visits (total  $N = 7388$  and  $N = 6138$  given positive utilization) and for hospitalization ( $N = 7676$  and  $588$ ) using a subsample from the Swiss Health Survey 2007 where individuals with a medical profession are excluded. We use the same set of controls as in Table 3 and the estimated coefficients do not differ much.

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