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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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Abstract

The focus of the present study is on consumer health information in relation to supplier induced demand (SID). We argue that previously used measures of consumer health information are not suitable to identify SID. Using a new information measure based on questions of the Swiss Health Survey, we estimate a Poisson hurdle model for office visits. We find that information has a negative effect on health care utilization, thus providing evidence for the SID hypothesis.

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 that conventional supply and demand models are not applicable to the health care market (Feldstein, 1970; Evans, 1974; Fuchs, 1978; Green, 1978). 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 serious misbehavior of health care providers (see e.g. Stano, 1987, or Labelle et al., 1994), even though a majority of economists and physicians suspect that health care providers induce demand (McGuire, 2000).

Although the central issue is well understood in theory, testing the SID hypothesis turns out to be quite difficult in practice. Van Doorslaer and Geurts (1987) use time-varying covariates to analyze the behavior of physicians facing financial incentives. Grytten and Sorensen (1999, 2001) compare physicians by their type of contract and Iversen (2004) as well as Grytten and Sorensen (2007, 2008) analyze the behavioral response of physicians to a patient shortage. However, the findings of these studies provide only indirect evidence for or against the SID hypothesis. In other words, there is no direct link between the empirical approach and the theoretical foundation of the SID hypothesis, i.e. the information asymmetry between patients and physicians. Two exceptions are Hay and Leahy (1982) and Kenkel (1990) where the empirical approach relies directly on the information gap. Hay and Leahy measure consumer health information by the occupation, i.e. individuals working in the health care sector are assumed to have more information on health services, and Kenkel uses survey questions about symptoms. Individuals with a high level of information are then supposed to be less prone to demand inducement, but the empirical findings suggest that information has a positive effect on health care demand.

The focus of the present study is to examine whether SID exists for physician services in Switzerland. We argue that medical occupation and symptom knowledge are inaccurate measures of consumer information. Using an unique measure of consumer information based on responses to survey questions about health competence, we estimate the demand for office visits 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 to test the SID hypothesis. Our empirical results indicate that the number of office visits 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 the theoretical background on consumer health information. Section 3 provides some details on the Swiss health care system and section 4 presents the data and the empirical approach. The key findings are discussed in section 5. Finally, the last section contains some concluding remarks and deals with some limitations of the analysis.

2 Consumer Health Information and the Demand for Health Care

The conceptual framework for our analysis is based on Grossmann's (1972) human capital model and is related to Dranove's (1988) model on the physician-patient relationship.[1] The former implies that medical care is considered as an input into the consumer's production of health and health itself is assumed to be a durable capital stock. An increase in health is directly associated with utility gains and indirectly due to greater efficiency of both leisure time and consumption. In this framework, the consumers decide on the utility maximizing investment in health based on the marginal benefits and costs of medical care. However, consumers have only imperfect information about their own health conditions, the marginal benefits of medical care, the provider quality and the choice among medical care alternatives. Therefore, health information is valuable to consumers since it enables them to improve decisions about medical care (Arrow, 1963; Kenkel, 1990). Note that the extent of consumers' information depends on the relation between the expected value of information and costs of acquiring information. The expected value and costs are determined by individual characteristics, e.g. the education level. In addition, more than one type of consumer health information has to be considered since purchasing medical care involves several decisions (see e.g. Kenkel, 1990). There

[1] In what follows, we assume that physicians are paid on a fee-for-service basis. This assumption ensures that physicians actually have an incentive to induce demand.

are at least three types of information (Haas-Wilson, 2001): First, diagnostic information denotes the patient's ability to determine what is causing illnessess and symptoms. Second, physician-specific quality information enables the patient to improve its provider choice in terms of quality and specialty. Third, treatment information denotes the patient's ability to distinguish between necessary treatment and induced demand.[2] Although all types of information are associated with improved decisions about medical care, only treatment information enables the patient to better evaluate the necessity of a recommended treatment. However, diagnostic information and physician-specific quality information could have an indirect effect on recommended treatments or demand for specific medical services, e.g. office visits. In addition, while conducting empirical investigations one has to carefully appraise which type of information is measured since e.g. diagnostic information may not be suitable to find evidence for or against the SID hypothesis. Therefore, we will discuss the theoretical as well as the observed effects of all types of consumer information on health care demand in more detail.

With respect to demand inducement, the central issue is the patient's ability to evaluate the treatment advice of the health care provider, e.g. a physician. In the model of Dranove (1988), supplier induced demand exists whenever physicians are better informed than their patients. In addition, one prediction of the model is an inverse relationship between inducement and the patient's treatment information. Using a game-theoretic approach, Xie et al. (2006) and De Jaegher (2012) extend the model of Dranove by introducing a patient population with heterogenous (treatment) information. According to the authors, an individual increase in patient information does not necessarily decrease demand inducement. To alter physician behavior, a sufficiently large fraction of the population has to be well-informed and the increase in the individual patient information has to be large enough, respectively.

While these theoretical results predict a (weakly) negative effect of consumer information on demand inducement, the empirical evidence is rather converse. Using medical occupation as proxy, Hay and Leahy (1982) find a positive effect of information on physician visits. However, medical

[2]The nomenclature of the different information types is not standardized throughout the literature. In particular, Dranove (1988) uses the term 'diagnostic skills' for the patient's ability to distinguish between necessary treatment and induced demand while Haas-Wilson (2001) uses the term 'diagnostic information' for the patient's ability to determine what is causing illnesses and symptoms. Note that we stick to the nomenclature of Haas-Wilson. Consequently, 'treatment information' denotes the patient's ability to distinguish between necessary treatment and induced demand.

professionals might 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. 'professional courtesy' (see Bunker and Brown, 1974). In addition, a treatment received by a medical professional might be 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. Therefore, medical occupation might be unsuitable to test the SID hypothesis since it is unlikely that the profession measures merely treatment information.[3] Based on survey questions about symptoms of four diseases, Kenkel (1990) finds a positive effect of information on utilization. However, knowledge of symptoms might rather improve the decision (process) to visit a physician than the patient's ability to distinguish between necessary treatment and induced demand. In fact, Kenkel concludes that information plays the dominant role in increasing the probability of health service utilization. Using data on health information searching behavior from non-physician sources and a measure for trust in physicians, Dwyer and Liu (2013) find a positive effect of consumer health information on the probability to visit a physician as well as the number of physician visits but a decrease in the probability to visit the emergency room. Although the estimated effects are consistent with previous results in the literature, searching for health information and being well-informed is not the same. Concretely, the former could be simply an indication of anxiety or risk aversion which affects both the probability to visit a physician and the number of visits. In addition, health information from e.g. the internet can result in a higher demand for health care services due to larger concerns about the own health, or consumers might lack the ability to understand the given information (see e.g. Suziedelyte, 2012). In summary, previous findings suggest that consumer information mostly increases health care consumption and, therefore, contradicts the theoretical implications. However, it is likely that the employed information measures are not suitable to test the SID hypothesis.

Although we focus on patient information given a strictly positive demand where SID can take place, the decision to visit a physician must also be taken into account since demand inducement is

[3]The idea to compare physicians (and their families) with other professional groups dates back to Bunker and Brown (1974) and has been extended by Domenighetti et al. (1993). However, their analysis is based on the fact that e.g. lawyers are considered by their physicians 'special patients' since lawyers might be able to cause more litigation. Thus, the similarity of the prevalence between physicians and other professional groups (compared to the rest of the population) and not the medical occupation per se is used to test the SID hypothesis.

probably affected indirectly. In particular, badly and well informed individuals in terms of diagnostic information and physician specific quality information could have different consumption patterns. First, Parente et al. (2005) and Hsieh and Lin (1997) show that knowledge of insurance benefits and (diagnostic) information, respectively, increase the demand for preventive care. Since preventive care is mostly associated with a decrease of either the probability or the severity of illness (see e.g. Phelps, 1978; Kenkel, 1994; Tian et al., 2010), the demand for curative care could depend negatively on preventive care. In addition, diagnostic information is likely to improve the patient's choice among health care provider alternatives, i.e. pharmacies, general practitioners, medical specialists, and hospitals (see e.g. Dwyer and Liu, 2013). Consequently, unnecessary follow-up visits due to inappropriate provider choices decrease with diagnostic information.[4] Second, patient's knowledge on provider reputation and quality affects both the behavior of the health care provider as well as the behavior of the patient. The empirical results suggest that high reputation enables providers to increase the price for their services (see e.g. Pauly and Satterthwaite, 1981; Haas-Wilson, 1990). Similarly, in a health care system with fixed fees, physicians with a high reputation might be able to increase the volume of (unnecessary) medical care without loosing patients. On the patient's side, Dafny and Dranove (2008) show that market shares of high quality Medicare HMOs increase as soon as consumers become aware of the quality differences. Consequently, private information on provider quality enables patients to make better choices. As a result, better informed individuals might demand more medical care since the marginal utility of one unit of high quality care is larger compared to low quality care. Given the arguments stated above, the indirect effect on health services utilization of diagnostic information is ambiguous. In addition, it is likely to be positive for physician-specific quality information. However, the crucial point is that an *observed* relationship between e.g. physician visits and one of these two types of consumer health information cannot be taken as evidence for or against the SID hypothesis.

As argued, previously used measures of health information are either unsuitable to find evidence for or against the SID hypothesis or have at least indirect effects on health care utilization that bias any estimated inducement effect. To solve this problem, we employ a unique measure of consumer information that is likely to capture the patient's ability to distinguish between necessary treatment

[4]Inappropriate health care provider choice might be only a minor issue as Atella and Deb (2008) recently found for Italy that primary care physicians and medical specialists are substitute sources of medical care.

and induced demand. Given the theoretical results by Dranove (1988), Xie et al. (2006) and De Jaegher (2012), our main hypothesis is that consumer information has a negative effect on health care utilization given that the demand is positive. In addition, we are able to test whether consumer information affects the decision to buy preventive care or substitutes office visits. Put differently, to some extent we are able to check whether our measure of consumer health information captures diagnostic information as well.

3 The Swiss Health Care System

The Swiss health care system is a mixture between competition enforcing elements and regulations on the federal as well as the cantonal (state) level.[5] The basic health insurance is mandatory for all Swiss residents, but is provided by private insurance companies. Although the health insurance providers are not allowed to make profits in the basic insurance, they can sell profitable supplementary insurance plans to their customers. General practitioners and specialists are generally self-employed, mostly paid on a fee-for-service basis (FFS) and individuals can freely choose their physician.[6] In addition, the health insurers are obliged to contract with every licensed health care provider. Note that the level of fees is a result from negotiation between health insurers and providers at the cantonal level. However, the general fee structure is established by the federal government. Furthermore, the government determines the coverage of the basic insurance as well as the selectable deductible levels and co-payment, and it approves the monthly premium. Thus, while the basic insurance coverage is fixed, individuals have some choice with respect to their cost sharing.

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 SID increases in insurance coverage. As the coverage of the Swiss basic insurance is large, SID might be large as well. In

[5]An extensive summary on the Swiss health care system is provided in the review of the Swiss Health System by the OECD (OECD/World Health Organization, 2011) and, in addition, by the European Observatory on Health Care Systems and the World Health Organization in the Health Systems in Transition (HiT) series (World Health Organization, 2000).

[6]Some insurance providers offer health plans where the individuals are bounded to a specific (group of) health care provider, e.g. HMO or PPO. According to the Swiss Health Survey, only 14.69% of 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.

addition, physicians paid on a FFS basis tend to induce demand while fixed salaries and HMOs with capitation 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 with limited possibilities to sanction for unnecessary services and malpractice. Consequently, the Swiss health care system and its features seem to be well-suited to test the SID hypothesis.

4 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 a random sample of the Swiss resident population aged between 15 and 99. The survey consists of a phone interview and an additional paper-based form, which was answered by 14'393 individuals. 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 primarily an extension in terms of health status and utilization of specialized medical services. Secondary, it adds data about the respondent's health expertise, labor market situation, and addiction. Table 1 provides variable definitions and descriptive statistics of both the dependent and the explanatory variables.

The measure for the individual's health expertise is constructed using answers to four questions about the respondent's 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 respondents 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 does not have the ability to evaluate health information. The other three questions were related to patient behavior in terms of communication e.g. with a physician, general knowledge about health issues and consumption behavior in terms of e.g. buying and using over-the-counter drugs. In all three questions, the range of possible answers was one (feel very certain) up to five (does not feel certain at all). We combined these four categorial 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 ability to evaluate the physician's advice. Kenkel (1990) proceeds in a similar fashion using ten questions about symptoms associated with diabetes, heart disease, cancer and tuberculosis. More recently, Hsieh and Lin (1997) use twenty questions about health effects and symptoms associated with high blood pressure and diabetes. While these information measures are quite objective but narrow due to the restriction on a few diseases, our information measure is more subjective but broader. In addition, we do not sum up the answers since we have categorial variables. According to the theoretical arguments, we expect *INFO* to have a negative effect on the number of office visits.

With respect to the empirical literature on SID, another important variable is the individual's occupation. In the following analysis, we use 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. The well-known positive relationship between physician density and demand for medical care is one of the starting points of the whole SID literature (Evans, 1974; Fuchs, 1978; Wilensky and Rossiter, 1983; Reinhardt, 1985; Stano, 1985; Cromwell and Mitchell, 1986) and still under consideration with respect to SID (see e.g. Carlsen and Grytten, 1998; Xirasagar and Lin, 2006; Peacock and Richardson, 2007). There are at least two possible explanations for this positive correlation. On the one hand, physicians may induce more demand in areas with high competition. On the other hand, physicians may settle down in areas with high demand. Even though the mentioned authors are aware of this endogeneity problem and commonly apply two-stage least squares, Dranove and Wehner (1993) show that this empirical approach fails to identify SID due to unsuitable instruments. In addition, more physicians in a certain area may lower the individual's cost of health care due to a better access. In fact, Auster and Oaxaca (1981) show that it is almost impossible to identify SID using the physician density. Moreover, using non-practice income Grytten et al. (2001) find for Norway some indirect evidence against the relationship of the physician density and SID. However, all 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 the number of physicians per thousand residents. The data is retrieved at the cantonal level from the Swiss Federal Statistical Office.

Altough 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. Note that the variable of interest, the number of physician visits, exhibits 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 for reasons of efficiency. 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

$$f(y_j) = \Pr(Y_j = y_j) = \frac{\Gamma(\theta + y_j)}{\Gamma(\theta)\Gamma(1 + y_j)} \left(\frac{\theta}{\theta + \lambda_j}\right)^{\theta} \left(\frac{\lambda_j}{\theta + \lambda_j}\right)^{y_j} \text{ for } y_j = 0, 1, 2, \ldots N \tag{4.1}$$

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 α 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. $\widetilde{\lambda}_j = \exp(x_j'\beta) \cdot \exp(\varepsilon_j)$ given the underlying assumption that $\exp(\varepsilon_j)$ follows a gamma distribution with mean one and variance α. The negative binomial distribution can then be obtained by inserting $\widetilde{\lambda}_j$ in the standard Poisson distribution. Finally, the resulting distribution in (4.1) 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 distribution collapses to the standard Poisson distribution. Since α has to be estimated, one can test whether the negative binomial model is appropriate or not.

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

$$f(y_j|y_j > 0) = \Pr(Y_j = y_j|y_j > 0) = \frac{f(y_j)}{1 - \left(\frac{\theta}{\theta+\lambda_j}\right)^{\theta}} \tag{4.2}$$

where $f(y_j)$ corresponds to the density given by (4.1) 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 $j = 1 \ldots n$ individuals have a positive utilization of medical services and the remaining $j = n+1 \ldots N$ individuals do not visit a physician. The likelihood of the entire sample is then given by

$$L = \prod_{j=1}^{n} \Pr(y_j > 0|x_j) \cdot f(y_j|y_j > 0, x_j) \times \prod_{j=n+1}^{N} \Pr(y_j = 0|x_j) \tag{4.3}$$

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

$$L_1 = \prod_{j=1}^{n} \Pr(y_j > 0|x_j) \times \prod_{j=n+1}^{N} \Pr(y_j = 0|x_j) \tag{4.4}$$

$$L_2 = \prod_{j=1}^{n} f(y_j|y_j > 0, x_j) \tag{4.5}$$

The first term depends solely on parameters in the hurdle component of the model, e.g. the binary choice visiting a physician. In contrast, 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 negative binomial model without loosing any information (see also Mullahy, 1998). Therefore, we estimate a logit model for the binary choice visiting a physician and a truncated negative binomial 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 affect 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 include 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, accident within the last year, and pregnancy during the last twelve months. 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. The descriptive statistics of the discussed variables as well as descriptions of additionally used controls are presented in Table 1.

Table 1: Variable definitions and descriptive statistics

Variable	Definition	Mean	Std. dev.
$PVISIT^a$	= 1 if the respondent visited a physician within one year	0.8091	
$VISITS^a$	number of physician visits within one year (including home visits)	4.0707	7.4797
$PPHARM^a$	= 1 if the respondent visited a pharmacy within one year	0.3674	
$PHARM^a$	number of pharmacy visits within one year	0.9142	2.0675
$PALT^a$	= 1 if the respondent used alternative medical care within one year	0.3177	
ALT^a	number of visits related to alternative medical care within one year	1.9358	6.0512
$DIAB^a$	= 1 if the respondent had tested his blood sugar level at least once	0.6775	
$OSTEO^a$	= 1 if the respondent had tested his bone density at least once	0.1223	
$CANC^a$	= 1 if the respondent had at least one checkup related to cancer	0.7461	
$PREV^a$	= 1 if the respondent has *DIAB*, *OSTEO* and/or *CANC* = 1	0.9123	
INFO	= 1 if the respondent as a high level of medical information	0.1759	
MEDOCC	= 1 if the respondent has a medical occupation, namely: physicians, dentists, oculists, pharmacists, and physiotherapists.	0.0386	
PDENS	number of physicians with practice per 1000 residents (by canton)	1.9928	0.5377
PHADENS	number of pharmacies and drugstores per 1000 residents (by canton)	0.3200	0.1187
SUBHLTH	self-reported health status (reference group: very good)		
good	= 1if the respondent reports health status as good	0.6680	
fair	= 1if the respondent reports health status as fair	0.1049	
poor	= 1if the respondent reports health status as pour	0.0272	
OBJHLTH	symptom-based health status, included 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; objective health is constructed by summing the indicators (range: 0 to 20, reference group: very good)		
good	= 1 for values 2 and 3	0.3381	
fair	= 1 for values 4 and 5	0.2417	
poor	= 1 for values between 6 and 20	0.1220	

continued on next page

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

Variable	Definition	Mean	Std. dev.
CHRDIS	= 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	0.5253	
ACCID	= 1 if the respondent had an accident at work, at home, road accident, and/or sporting accident	0.1184	
PREGN	= 1 if the respondent was pregnant within the last 12 months	0.0082	
MAJDEP	= 1 if the respondent suffers from clinical depression	0.0516	
DEDUCT	insurance deductible (reference group: below CHF 1000)		
medium	= 1 if the respondent has a deductible from CHF 1000 up to CHF 2000	0.2488	
high	= 1 if the respondent has a deductible above CHF 2000	0.1466	
ADDINS	= 1 if the respondent has an additional insurance for alternative medicine	0.5700	
EMPL	gainfully employed (reference group: fully employed)		
part-time	= 1 if the respondent reports part-time working	0.2445	
non	= 1 if the respondent reports to be non-working	0.3859	
GENDER	= 1 if the respondent is female	0.5617	
AGE	age category of the respondent (reference group: 15 to 30)		
36 - 50	= 1 if age between 36 and 50	0.2910	
51 - 65	= 1 if age between 51 and 65	0.2560	
>65	= 1 if age above 65	0.2202	
HLTHATT	= 1 if the respondent reports that health and healthy behavior is important for her lifestyle	0.8863	
INCOME	monthly income of the entire household (reference group: very low)		
low	= 1 if the respondent reports income of CHF 4500 - 5999	0.1816	
medium	= 1 if the respondent reports income of CHF 6000 - 8999	0.2914	
high	= 1 if the respondent reports income of CHF 9000 and more	0.2562	
HMO, PPO[b]	= 1 if the respondent has a HMO or PPO health plan	0.1469	
SUPPINS[b]	= 1 if the respondent has a supplementary insurance for hospitalization	0.7288	
BMI[b]	body mass index = weight in kilos divided by height in meters squared	24.320	4.0515
MIGR[b]	= 1 if the respondent has a migration background	0.2768	
COUPLE[b]	= 1 if the respondent is not single	0.6480	
NBKIDS[b]	number of childern in the household	0.4194	0.8389
MOUVPHY[b]	frequency of physical activity per week (reference group: never)		
sometimes	= 1if respondent reports once or twice a week	0.4379	
frequent	= 1if respondent reports three or more times per week	0.4020	
SMOKE[b]	= 1 if the respondent is a smoker	0.2607	
ALCO[b]	= 1 if the respondent drinks alcohol	0.8549	
DRUG[b]	= 1 if the respondent abused (illegal) drugs during the past two years	0.0387	
EDUC3[b]	education level (reference group: mandatory school)		
secondary	= 1 if respondent completed a secondary education	0.6037	
tertiary	= 1 if respondent completed a tertiary education	0.2758	
DETPSY[b]	= 1 if the psychological distress of the respondent is average or high	0.1676	
MASTERY[b]	mastery level of the respondent based on 3 questionnaire (reference group: weak control)		
average	= 1 if the respondent has average control	0.4001	
strong	= 1 if the respondent has strong control	0.3891	
IHELP[b]	= 1 if the respondent received informal help given daily difficulties	0.1203	
MSREG14[b]	degree of urbanisation (fourteen categories)		

[a] dependent variables

[b] The corresponding coefficients are not reported in the results tables in this article. Full tables of results can be found in the Online Appendix B.

5 Results

Table 2 reports the main results of the logit estimation for the hurdle part given by the likelihood in (4.4) and estimates obtained from the truncated negative binomial model for the count part given by the likelihood in (4.5).[7] In the estimation of the count component, the *INFO* coefficient is significantly negative on the 1% level and suggests a reduction of 0.55 physician visits per year. In addition, the estimated coefficient is not significantly different from zero in the hurdle component. Hence, being well-informed is unlikely to alter the overall demand. But in case of positive health service utilization, it seems to reduce the number of office visits. This suggests that our information measure captures rather the ability to evaluate the physician's advice than e.g. a preference for health care. Therefore, we conclude that there is evidence for SID. Contrary to the findings of Bunker and Brown (1974) and Hay and Leahy (1982), our results suggest that medical professionals have a significantly lower overall demand as the coefficient of *MEDOCC* is negative and significant on the 1% level in both the hurdle and the count component. This provides some evidence that individuals working in the health care sector have another consumption pattern than non-medical professionals due to e.g. access to informal care. Therefore, we conclude that medical occupation is unsuitable to test the SID hypothesis. Finally, the density coefficient in the hurdle component has a positive effect on utilization. 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 indicating that there is no relationship between office visits and the number of physicians in a certain area.

As expected, better health leads to a lower probability of visiting a physician and less utilization given positive demand. Moreover, the magnitude of the effect increases when health status is further decreased. In particular, poor subjective health status perfectly predicts the probability to visit a physician. In addition, chronic diseases, an accident, pregnancy and major depression have a positive effect on both the probability and the number of office visits. While the additional insurance is associated with and increase in the number of office visits, a higher deductible reduces

[7] Note that the estimated α is 1.595 and, given a standard error of 0.151, significantly different from zero. Hence, the choice of the negative binomial model compared to the standard Poisson model is appropriate.

Table 2: Hurdle model estimates

VARIABLE	HURDLE		COUNT	
INFO	-0.01106	(0.01428)	-0.55079***	(0.20787)
MEDOCC	-0.07403***	(0.02544)	-1.23914***	(0.36325)
PDENS	0.04889***	(0.01551)	0.12605	(0.21270)
SUBHLTH				
good	0.02106	(0.01377)	0.74476***	(0.18104)
fair	0.11791***	(0.02506)	2.73308***	(0.46669)
poor			7.83676***	(1.73166)
OBJHLTH				
good	0.03487**	(0.01388)	0.66911***	(0.22393)
fair	0.06773***	(0.01599)	1.00309***	(0.24808)
poor	0.12320***	(0.02270)	1.39256***	(0.33368)
CHRDIS	0.11041***	(0.01275)	1.67858***	(0.21988)
ACCID	0.17967***	(0.02608)	1.47211***	(0.26308)
PREGN			2.27778***	(0.42217)
MAJDEP	0.16070***	(0.03377)	2.05344***	(0.46392)
DEDUCT				
medium	-0.06339***	(0.01364)	-0.93236***	(0.19132)
high	-0.11124***	(0.01700)	-0.98297***	(0.26416)
ADDINS	0.01157	(0.01189)	0.87921***	(0.19118)
EMPL				
part-time	0.03981***	(0.01526)	0.77427***	(0.22641)
non	0.02616	(0.02032)	1.25571***	(0.31077)
GENDER	0.10892***	(0.01387)	0.07436	(0.21884)
AGE				
36 - 50	-0.04700***	(0.01516)	-0.85493***	(0.27669)
51 - 65	-0.03660**	(0.01792)	-0.93551***	(0.33105)
$>$ 65	0.04492*	(0.02458)	-1.01315**	(0.42280)
HLTHATT	0.06505***	(0.01813)	0.95762***	(0.28821)
INCOME				
low	0.04611**	(0.02211)	0.01277	(0.28102)
medium	0.06705***	(0.02129)	0.17326	(0.28159)
high	0.10691***	(0.02197)	0.49739	(0.33078)

$^{***}p \leq 0.01$, $^{**}p \leq 0.05$ and $^{*}p \leq 0.10$

Marginal effects after estimation of a truncated negative-binomial hurdle model for physician visits (total $N = 9804$ and $N = 7967$ given positive utilization) within one year using data from the Swiss Health Survey 2007. Robust standard errors in parentheses. Additionally controlling for the variables described in Table 1, see Online Appendix B for further details.

the probability to visit a physician as well as the utilization. Note that income and being female positively affects the probability of visiting a physician, but has no effect on the number of visits. Most of the described effects are statistically significant on the 1% level and, at least in terms of the sign, similar to the results of Kenkel (1990). The latter statement holds also for the estimated effect of age, which is particularly interesting since it exhibits a somehow counterintuitive negative sign. One possible explanation is a high correlation between age and the included health measures, which probably capture the health status very well. Another possibility is that the older individuals substitute physician care with other medical services (e.g. hospital care) or the elderly receive basic care in e.g. the retirement home which might decrease the need for physician's services.

The three main results with respect to the SID hypothesis as well as the other estimated effects are robust against several changes in the model specification and estimation method. First, we reduce the number of controls from 32 to 12 and estimate the negative-binomial model again. Second, we estimate the count part of the hurdle model with ordinary least squares, a negative-binomial model without truncation at zero and Tobit. In addition, we estimate the (zero-truncated) Poisson model without taking the overdispersion into account. The corresponding estimates are shown in Table A.1 and A.2 in Appendix A. They are comparable to our main results in terms of sign, but less precisely estimated. The latter is not surprising, since the other estimation methods are less efficient compared to the negative-binomial model. Finally, we test several specifications of the *INFO* variable in terms of considered questionary answers (out of four) 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.

While most of the variables used exhibit expected results, our estimation method and information proxy have some drawbacks. First, information might be endogenous due to e.g. unobserved heterogeneity that drives both demand for medical services and process acquiring health information (see Dwyer and Liu, 2013). Therefore, we follow Kenkel (1990) and apply the method described in Wooldridge (2002, p. 663 - 668) to replicate Kenkel's results using the present data. In short, we regress *INFO* on the full set of covariates and use the predicted residual in the estimation of the number of physician visits. We additionally include the inverse mills ratio, *lambda*, to correct for sample selection. The standard errors are then bootstrapped using 2000 iterations. As it is evident from Table A.4, the estimated coefficients are not considerably different from the main results presented in Table 2 but less precisely estimated. In particular, though the coefficient of *INFO* is negative and somewhat larger in absolute terms, it is not statistically different from zero. However, the fundamental question is whether endogeneity is indeed a problem. Since the coefficient on the residuals from the first step, *IRES*, equates 1.172 with a standard error of 2.223, we do not reject the null hypothesis that *INFO* is exogenous (see Wooldridge, 2002, p. 665). In other words, endogeneity is not an issue and our approach seems to be appropriate.

Second, regarding the underlying questions in the questionnaire, *INFO* might capture more than just the consumer's ability to evaluate the (treatment) advice of the physician. In particular, a consumer with a high level of health information might either make better choices in terms of health care services (e.g. visit the pharmacy instead of the physician) or seek more preventive care which in turn reduces the probability and severity of certain illnesses. Therefore, we estimate the hurdle model for pharmacy visits and the utilization of alternative medical services. In addition, we estimate binary choice models (logit) for preventive care related to diabetes, osteoporosis, cancer and an aggregate of these three measures. As it is evident from the corresponding in Table A.3, *INFO* does not affect the probabilites of using substitutes or preventive care and has no effect on the number of visits of the considered substitutes for physician services. Although we do not jointly estimate the consumer's demand for preventive care, physician's services and alternative medical care, these results provide some evidence that *INFO* captures only the ability to evaluate the (treatment) advice of the physician.

Besides these concerns about the information measure, our analysis exhibits some limitations. The outcome variables are rather raw measures for the utilization of medical services and we cannot control the length of a visit, its quality and the effect on the individual's health. Some unobserved quality differences that e.g. affect the demand and are correlated with *INFO* would bias the estimates and might invalidate our conclusions. However, this would only materialize if the bias is so large that the sign changes. 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 several times to visit the physician once (per decision). Second, in some estimations the sample size is reduced to 7828 observations due to missing data. In particular, unreported income and deductible level account for nearly two thirds of the missing data. In addition, questions on supplementary insurance, chronic diseases and accidents are 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 9804 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 previously applied health information measures for testing the SID hypothesis remains valid and our empirical findings support this view.

6 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 demand 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 idea seems straightforward, finding an acceptable measure for information can be difficult. As we have argued, medical occupation and symptom based information measures appear to be inappropriate since the utilization of health care services of individuals with high information in this sense is probably altered through other channels than just the resistance against demand inducement. Consequently, these information measures are unsuitable to test the SID hypothesis. Nevertheless, with an information measure that captures only treatment information that is used by the patient to judge the behavior 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, they have a lower probability of using medical services and use less of these services, implying that their *overall* demand is smaller. Second, less informed people tend to have a higher utilization of medical services, which supports the SID hypothesis. Moreover, the fact that information measured in this way does not affect the likelihood of buying health care at all supports this view. In summary, our discussion suggest that medical occupation (and symptom based measures) cannot be used to test for SID but it is still possible to identify it with an alternative information 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 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 such that insurers can sanction providers who induce demand.

There are some limitations to the approach taken in this paper. In particular, office visits is a rather raw measure of health care utilization, we cannot account for quality differences of health care and our information proxy could measure somehow the communication skills of the patient. If she can express herself more accurately, the physician might give her a more appropriate treatment which results in fewer follow-up visits. In addition, we do not distinguish between follow-up consultations and several independent consultations due to the hurdle model approach. These issues might be resolved by using more detailed 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.

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A Additional Results

Table A.1: Hurdle model with less controls

	HURDLE		COUNT	
INFO	-0.00126	(0.01335)	-0.35020*	(0.19314)
MEDOCC	-0.06585***	(0.02218)	-0.98449***	(0.35628)
PDENS	0.03200***	(0.01024)	0.20997	(0.12770)
SUBHLTH				
good	0.02031	(0.01254)	0.79766***	(0.15778)
fair	0.12475***	(0.02120)	2.95956***	(0.41305)
poor	0.22206***	(0.01077)	8.35165***	(1.41416)
OBJHLTH				
good	0.03396***	(0.01263)	0.59343***	(0.20346)
fair	0.06617***	(0.01410)	0.98645***	(0.21771)
poor	0.10785***	(0.02057)	1.49921***	(0.29118)
CHRDIS	0.11314***	(0.01159)	1.72035***	(0.20267)
ACCID	0.18271***	(0.02364)	1.45351***	(0.23908)
PREGN			2.58663***	(0.37926)
MAJDEP	0.11139***	(0.03251)	2.29099***	(0.39601)
DEDUCT				
medium	-0.05063***	(0.01215)	-0.91406***	(0.18004)
high	-0.09330***	(0.01544)	-1.02429***	(0.22878)
ADDINS	0.02388**	(0.01039)	0.76149***	(0.17305)
EMPL				
part-time	0.02917**	(0.01325)	0.63923***	(0.20859)
non	-0.00117	(0.01903)	1.03093***	(0.26385)
GENDER	0.10208***	(0.01189)	-0.08749	(0.20101)
AGE				
36 - 50	-0.03121**	(0.01376)	-0.74372***	(0.24521)
51 - 65	-0.01687	(0.01551)	-0.67418**	(0.28607)
$>$ 65	0.05313**	(0.02122)	-0.83000**	(0.33198)
HLTHATT	0.06719***	(0.01563)	0.74307***	(0.25773)

$^{***}p \leq 0.01$, $^{**}p \leq 0.05$ and $^{*}p \leq 0.10$

Marginal effects after estimation of a truncated negative-binomial hurdle model for physician visits (total $N = 9804$ and $N = 7967$ given positive utilization) within one year using data from the Swiss Health Survey 2007. Robust standard errors in parentheses.

Table A.2: Count component estimates

	INFO		*MEDOCC*		*PDENS*	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Regression	-0.41003*	(0.23355)	-1.06667***	(0.28533)	0.09272	(0.28723)
Poisson	-0.43135*	(0.24453)	-1.26875***	(0.34876)	0.05520	(0.26605)
Zero-trunc. Poi.	-0.45175*	(0.25963)	-1.38664***	(0.38912)	0.04891	(0.27804)
neg-bin	-0.50122**	(0.20799)	-1.19191***	(0.33151)	0.12907	(0.21382)
Tobit	-0.41003*	(0.23253)	-1.06667***	(0.28409)	0.09272	(0.28599)

$^{***}p \leq 0.01$, $^{**}p \leq 0.05$ and $^{*}p \leq 0.10$
Marginal effects for main variables of interest after estimation of the count component given by (4.5) by OLS as well as under the assumption of a Poisson distribution, a zero-truncated Poisson distribution, and a negative-binomial distribution and by Tobit. The estimation is based on the Swiss Health Survey 2007 and $N = 6483$. Robust standard errors in parentheses. We use the same set of controls as in Table 2. Full tables of results are provided in the Online Appendix B.

Table A.3: Substitutes and Prevention

	INFO		*MEDOCC*		*PDENS*	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Pharmacy						
HURDLE	0.02367	(0.01840)	-0.13356***	(0.03417)	-0.01581	(0.01887)
COUNT	0.10106	(0.13359)	0.63194	(0.39045)	0.10928	(0.13566)
Alternative med.						
HURDLE	-0.00101	(0.01479)	0.04390	(0.02805)	0.02989*	(0.01621)
COUNT	0.01818	(0.53046)	0.58840	(0.70972)	-0.35908	(0.58913)
Prevention						
Diabetes	0.01548	(0.01728)	0.10462***	(0.03366)	0.04262**	(0.01777)
Osteoporosis	0.00441	(0.01016)	0.01228	(0.02439)	0.01341	(0.01149)
Cancer	0.02084	(0.01435)	0.00121	(0.03243)	0.00126	(0.01490)
overall	0.01385	(0.01232)	0.05117*	(0.02822)	0.02388*	(0.01276)

$^{***}p \leq 0.01$, $^{**}p \leq 0.05$ and $^{*}p \leq 0.10$
Marginal effects for main variables of interest after estimation of a truncated negative-binomial hurdle model for pharmacy visits (total $N = 7956$ and $N = 3086$ given positive utilization) and consumption of alternative medical care ($N = 8133$ and $N = 2053$) within one year using data from the Swiss Health Survey 2007. In addition, marginal effects after estimation of a binary choice model (logit) for preventive medical care consumption related to diabetes, osteoporosis, cancer and a combined measure ($N = 8087$, $N = 6360$, $N = 8098$, and $N = 8105$, respectively). Robust standard errors in parentheses. We use the same set of controls as in Table 2. Full tables of results are provided in the Online Appendix B.

Table A.4: Endogeneity Analysis

	Dependent Variable			
	(1) INFO		(2) VISITS	
IRES			1.17206	(2.22259)
lambda			-4.98685***	(1.23783)
INFO			-1.39261	(2.23796)
MEDOCC	0.14620***	(0.02678)		
EDUC3				
secondary	0.04843***	(0.01510)		
tertiary	0.07328***	(0.01713)		
PDENS	-0.00835	(0.00730)	0.01702	(0.12903)
SUBHLTH				
good	-0.01017	(0.01133)	1.08137***	(0.24278)
fair	-0.02643	(0.01968)	2.76102***	(0.39576)
poor	-0.05948**	(0.02413)	3.63639**	(1.56657)
OBJHLTH				
good	-0.00082	(0.01122)	0.19455	(0.23444)
fair	-0.03192***	(0.01166)	0.33758	(0.26949)
poor	-0.02435	(0.01603)	0.88473***	(0.32731)
CHRDIS	-0.00935	(0.00937)	0.65894***	(0.27783)
ACCID	-0.01006	(0.01272)	0.39800	(0.29102)
MAJDEP	-0.03867**	(0.01766)	1.47224***	(0.36270)
DEDUCT				
medium	-0.00686	(0.01115)	-0.34885	(0.21968)
high	0.02185	(0.01430)	0.04910	(0.33822)
ADDINS	0.03358***	(0.00886)	0.61289***	(0.18802)
EMPL				
part-time	0.04370***	(0.01237)	0.32567	(0.25293)
non-working	0.02374*	(0.01312)	0.46040*	(0.25923)
GENDER	0.00547	(0.01039)	-0.44297**	(0.22322)
AGE				
36 - 50	0.05723***	(0.01124)	-0.16860	(0.24390)
51 - 65	0.11326***	(0.01257)	-0.13508	(0.35510)
$>$ 65	0.09648***	(0.01478)	-0.16183	(0.36369)
INCOME				
low	0.00528	(0.01328)	0.35620	(0.24793)
medium	0.01830	(0.01166)	0.07290	(0.23710)
high	0.04677***	(0.01250)	-0.03421	(0.28375)
HLTHATT	0.08459***	(0.01070)	-0.00023	(0.34579)

$^{***}p \leq 0.01$, $^{**}p \leq 0.05$ and $^{*}p \leq 0.10$

(1) Regression of INFO on the given covariates using data from the Swiss Health Survey 2007 (N = 12231) to get predictions for the residuals, *IRES*. The latter is used together with the inverse mills ratio, *lambda*, in the estimation of the count part (2) (negative binomial model, N = 9727). The presented results for the count part (2) are marginal effects with bootstrapped standard errors using 2000 iterations.

B Online Appendix

Supplementary tables to this paper can be found on the homepage of the corresponding author: http://staff.vwi.unibe.ch/schmid/downloads/sid_online_appendix.pdf