Capacity as a Determinant of the Supply for Physicians' Services

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Abstract

The supply of physicians' services is determined by both, clinical factors and the economic environment. We present a model of physicians' behavior and test its predictions as well as its assumptions using Swiss micro data. We show that capacity is an important factor for physicians' decisions of how much medical services they supply. Furthermore, we propose a simple method to compare the different distributions of certain services across physicians.

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1 Introduction

We consider health care services in Switzerland. This market displays some special features on both the supply and the demand side. On the supply side, the provision of health care is strongly regulated. Prices arise from a negotiation process between insurance companies and physicians. Not only do they discuss the price level but they also define the units of services. This involves a lot of medical know-how and sets a state of the art. Each medical problem requires at least one service. The relation between the medical problem and the corresponding set of services defines the state of the art. Prices and services are published in an official fee schedule to which the government has to agree. On the demand side, all patients are insured so they do not have to pay directly the full price for the services purchased.

The relationship between a physician and her patient is characterized by an expert/client relationship. The physician as the expert both advises a client about required services and offers to supply the recommended services for a fee. In addition, health is a complex good which cannot be sold directly. Patients purchase the intermediary good health services that should improve their health status. Nevertheless, it is often impossible to infer from a health status to a potentially wrong therapy. Control mechanisms are, therefore, poor. This raises the question whether physicians take too much advantage of their dual role as supplier and adviser. In the literature, this question is discussed under the term of supplier-induced demand (SID).

We present a theoretical model for the market of physicians' services which allow for these special features. In addition, we test the theoretical assertions empirically with the help of data that origin from a large health insurance company in the city of Basle.

Gaynor (1994) provides an overview of the SID literature. He reviews both theoretical and empirical papers investigating the implications of induced demand in terms of information or incentives. Theoretically, Pauly (1980) analyzes the physician-patient relationship as an agency relationship. He shows that a utility maximizing physician induces demand by choosing a lower level of accuracy of her diagnosis. Dranove (1988) presents an inducement model in which the physicians are bound by the beliefs of the patients. He shows that even if the patients know the physician's recommendation strategy, the latter has an incentive to recommend unnecessary treatment. Accordingly, the patient cannot avoid SID. Wolinsky (1993, 1995) and Emons (1997) explicitly model equilibrium in the market for experts' diagnostic and treatment services. They both find multiple equilibria with and without fraud. Wolinsky (1995) identifies equilibria with fraud, despite intese competition between experts. Emons (1997) shows that market equilibria with nonfraudulent behavior exist if consumers rationally process ex ante information such as prices and capacity.

The empirical evidence on SID is equivocal. Some studies examine the influence of information levels of patients on market performance. Intriguingly, the results of American studies differ from the results of a European study. Bunker and Brown (1974), Hay and Leahy (1982) and Kenkel (1990) disclose a positive relationship between patients' information level and demand for health services. Domenighetti et al. (1993), however, find the contrary: physicians and their relatives show a significantly lower rate of surgical procedures than the population average. The same finding holds for lawyers and their families.

Other empirical studies concentrate on the physicians' incentives. Numerous studies examine the incentive effects of cesarean section rates and vaginal delivery rates, respectively. Keeler and Fok (1996) find little effect of physicians' fee schedules on cesarian rates. Brown (1996) investigating the leisure demand of the physicians as an incentive in favor of cesarian section deliveries rejects the hypothesis that non-clinical variables are irrelevant. Grytten et al. (1995) compare contract physicians and community physicians whose incentives differ.[1] They only find evidence for SID concerning laboratory tests.

Labelle et al. (1994) present a conceptual framework for SID. They consider two dimensions of the effectiveness of the agency relationship and the effectiveness of services utilized. The first dimension is a standard question in the SID literature asking whether a patient would have demanded the service if she had the same information as the physician. The second dimension is not a common consideration in the SID literature as it is independent of the agency problem. Here, the question is whether a service contributes positively to the patient's health status. Consequently, they discuss four different kinds of SID based on the respective answers. Interestingly, Labelle et al.

[1] Contract physicians are self-employed and receive a fee for service, whereas community physicians are employees of the municipality and are paid an hourly wage.

(1994) even detect SID when both questions can be answered affirmatively. As a result, certain services may be demanded by the fully informed consumer and contribute to her health status. Nevertheless, these services should not be provided because they are too expensive. Accordingly, some types of health care may be abandoned in favor of others, because of their costs.

In this paper we theoretically and empirically investigate incentives generated by capacity utilization. In general, SID is present when a physician influences the demand for health services in an undesirable manner. We examine whether idle capacity leads to demand inducement by the physicians. The theoretical framework, which is inspired by the special features of the Swiss market for health services, reveals a strong incentive for demand inducement in case of idle capacity.

The basic assumptions in our model are that physicians are price takers and maximize profits. Due to the fixed set-up costs of the practice, a markup is necessary to break-even. All physicians face the same expected demand function in the model. This assumption is justified since all physicians potentially provide the same services and are not permitted to advertise. Accordingly, they face a random sample of patients exogenously given to them. Physicians who face a low realization of their stochastic demand such that they have idle capacity will sell unnecessary treatment to their patients in order to utilize capacity. Consequently, the theoretical model predicts, that the physicians sell additional, unecessary services up to the point of full capacity.

The empirical part of the paper tests the hypothesis of SID. The definition of SID is also based on the features of the Swiss health market, where all consumers have basic health insurance. When a service is beyond the state of the art in the sense of the fee schedule we speak of SID. In this case, we are dealing with a case of SID, although a patient may demand these services. For instance, a patient may demand a complete blood picture after a normal flu. Whenever the insurance company has to pay for such services, we identify SID. Therefore, we replace the economic optimum in the sense of Labelle et al. (1994) by the state of the art.

The data consist of general practitioner (GP) services of units delivered which are covered by health insurance. Naturally, the state of the art is not observable. We assume that the average physician represents the state of the art. Accordingly, SID is a deviation from the mean. Using capacity indicators as well as SID indicators we are able to identify such a deviation from the mean as SID. Furthermore, we confront the crucial assumptions of the model with the data. First, a possible heterogeneity of the physicians concerning their potential supply does not change the results. Second, the heterogeneity of the physicians' patient population captured by the age does not affect the results either.

The model predictions are confirmed by the data. Capacity is an important factor for physicians' decisions of how much medical services they supply. Accordingly, the hypothesis of SID cannot be rejected.

The remainder of the paper is organized as follows. In section 2 we outline a model of the market for physicians' services. We show that physicians with idle capacity induce demand. Section 3 introduces the data and the main variables under consideration. Section 4 identifies indicators for idle capacity and demand inducement. In section 5, the Central Limit Theorem (CLT) is applied in order to compare the physicians in the data. In section 6 we present our empirical results. Finally, section 7 discusses our findings and concludes. The sample statistics and additional results are relegated to the appendix.

2 The model

Consider a market for health services. The market consists of I physicians, indexed $i \in \{1, 2, ..., I\}$, who are the suppliers. Each physician owns a practice. The fixed set-up costs of the practice are $F > 0$. Each physician works up to T hours, i.e., her capacity constraint is given by T hours of work. The physician's break-even wage is F/T. Each physician is a price taker. The average price for an hourly treatment is denoted by $\overline{p}$, with $\overline{p} \geq F/T$. Prices are fixed within a fee schedule and, therefore, common knowledge.

The demand side of the market consists of M consumers, indexed $j \in \{1, 2, ..., M\}$. Consumers differ with respect to their (subjective) health status.[2] This status is randomly distributed across consumers with a finite mean and a finite variance.

Following Krämer (1981) we split the good 'physician's health services' into two activities. The first activity is 'seeing a doctor'. This decision is a zero–one-choice by

[2]It is possible to include varying preferences among consumers with no additional insights.

the consumers. Each consumer j has a reservation price v_j for this activity. This price v_j depends on the health status and on her opportunity costs. If v_j is higher or equal to the price for an expected treatment, she decides to see a physician and becomes a patient. There are N patients, with $N \leq M$, in the market. The demand curve is decreasing in $\overline{p}$. The diversity in health status and the large number of consumers assure the assumption of a continuous demand function.

Only if a consumer decides to see a physician, she consumes the second activity 'services of the physician' and is willing to pay the price for it. The treatment consists of several services that are chosen by the physician. Owing to the information asymmetry between physician and patient, the extent of this treatment is determined by the physician (see Emons 1997). A patient who does not have the professional knowledge cannot distinguish between different services and buys the treatment as a whole package. Accordingly, once she decides to see a doctor, she is willing to accept what the physician proposes. In Switzerland, this assumption is also supported by the kind of contracts insurance companies offer to their customers. When a patient needs health services, each year she must pay the first 150 sFr. Only 10% of the amount exceeding these 150 sFr. must be paid by the patient. That is, the first activity of seeing a doctor is the most expensive one. Additional services are, therefore, sold with a 90%-discount. Furthermore, patients do not oppose their physician's opinion. Due to the credence property of the good 'health services', patients are forced to follow the advice of the physician or reject it as a whole. When they do not agree with her they just change their physician (see Wolinsky 1993).

Suppose that all physicians provide the same services. Accordingly, they do not differ concerning their medical specialization. Each physician faces a random sample of the whole patient population. Denote the patients per physician by n_i. Each patient j sees only one physician.[3] Consequently, $\sum_{i=1}^{I} n_i = N$. We assume homogeneous patient populations across physicians. Each physician faces an identically distributed demand for every single service. The distribution may vary across services but for a given service the demand is identically distributed across physicians. The demand without SID for health services is only a function of the patient's health status. A

[3] This assumption is confirmed by the data: Only 3% of the patients went to see more than one physician.

physician who does not induce demand just reacts to a random process. She faces a sample of patients and treats them according to the state of the art.

On the average it takes $\overline{t}$ hours time to treat a patient. Consequently, we assume that all physicians face the following marginal cost structure of their services:

$$MC_i = \begin{cases} 0 & \text{if } n_i\overline{t} \leq T \\ \infty & \text{if } n_i\overline{t} > T \end{cases}.$$

This cost structure can be explained as follows. As long as the capacity constraint is not binding the physician has marginal costs of zero. The investment in her practice is sunk. If, however, the physician faces too many patients, she reaches the capacity constraint T. Accordingly, marginal costs become infinite.

Given the sunk costs F, the maximum working hours T, and the exogenously given prices $\overline{p}$, each physician maximizes her profits. In order to maximize profits the physician determines two variables: her number of patients n_i as well as the amount of demand inducement per patient d_i. In the first place, physician i faces $\widetilde{n}_i$ patients. $\widetilde{n}_i$ is an exogenous variable to her. Then, she chooses n_i, the number of patients that she actually treats. This means, she sets $n_i = \widetilde{n}_i$, if $\overline{t} \cdot \widetilde{n}_i \leq T$, and $n_i < \widetilde{n}_i$, otherwise. Accordingly, a physician only has the possibility of rejecting or accepting patients. A physician with $\overline{t} \cdot \widetilde{n}_i > T$ randomly rations among her potential patients before knowing their health status. The rejected patients of physician i become part of $\widetilde{n}_{j \neq i}$. It is important to note that in Switzerland physicians cannot acquire additional patients as any kind of advertisement is forbidden. The variable d_i defines the amount of demand inducement per patient, measured by additional services sold. According to her profit maximization behavior, she chooses $d_i > 0$, if $n_i\overline{t} < T$, and $d_i = 0$, otherwise.

- insert figure 1 about here -

Figure 1 shows the intuitive explanation for the choice of the exact level of n_i and d_i. The figure depicts the market for health services in the price/quantity space where quantity is measured in hours. The supply curve of health services is completely elastic up to T. For $q > T$ it becomes inelastic. The negative slope of the demand curve is due to the service 'seeing a doctor' which depends negatively on prices. In figure 1, physician 1 has just enough patients to fully utilize her capacity. The market clears at the price $\overline{p}$. Consequently, she has no incentive to induce demand. Physician 2, however, has too few patients. If she induces demand on her patients, she is able to work at full capacity. The market would not clear at the price $\overline{p}$ for physician 3. This physician would like to raise prices but she is not allowed to do so. Accordingly, she randomly rejects a number of patients such that her capacity constraint is binding. It is actually possible for her to treat too many patients but there is no additional money to earn. In order to treat too many patients she has to reduce her services per capita which offsets the gains of treating more patients. Moreover, by treating a patient within a shorter average time of treatment, e.g., $d < 0$, a physician 3 runs into liability problems. It is easier to detect too little treatment than too much treatment though the control mechanisms are weak.

If a physician does not induce demand, i.e., $d_i = 0$, she chooses a diagnosis and a therapy according to the state of the art. In this case, she simply reacts to a random process: she has a sample of patients $\widetilde{n}_i$ and provides the necessary treatment. The expected price for a treatment is then $\overline{t}\,\overline{p}$ which is also her expected turnover per patient. In contrast, if she chooses to induce demand in order to increase her income, she increases the average treating time from $\overline{t}$ to $\overline{t} + d_i$. During the additional time d_i she does not harm her patient, but sells unnecessary treatment. She ends up with an expected turnover per patient of $(\overline{t} + d_i)\,\overline{p}$. A treatment is unnecessary if either the patient, provided that she is equally well informed as the physician, would not demand, or if it is not part of the performance based on the fee schedule that health insurance and physicians worked out.[4] In other words, an unnecessary treatment is beyond the state of the art. Nevertheless, a physician's high turnover cannot be explained at the outset. She either induces demand or she has a high realization of the random variable, i.e., her patients are particularly sick. Summarizing, we conclude with

Observation 1 Physicians choose their number of patients n_i and their level of demand inducement per patient d_i in order to utilize their capacities, i.e.,

$$n_i = \begin{cases} \widetilde{n}_i & \text{if } \widetilde{n}_i \overline{t} < T \\ T/\overline{t} & \text{otherwise} \end{cases} \quad \text{and} \quad d_i = \max\left\{T/\widetilde{n}_i - \overline{t}, 0\right\}.$$

[4]Hypochondriac demand is not subject to the fee schedule, e.g., an insurance company does not have to pay for monthly check ups of (physically) healthy people.

3 The data

Our data are provided by a large health insurance company. These data origin from Basle the second largest city in Switzerland. The company's market share in Basle is more than 40%. The data covers 81 physicians in the year 1994. They are all GPs working in the city of Basle. To be categorized as GP the share of specialized treatments on the overall turnover has to be less than a certain threshold. This ensures that our data contain no specialists disguised as GPs. The 81 physicians represent about 90% of all genuine GPs in Basle.

The primary data set consists of 8544 patients. It contains all the bills per physician for each patient. The main data set includes all 81 physicians. In contrast to the primary data set, the observation is defined as a physician not a patient. These micro data consist of the number of patients each physician treats, the average age of the patients and the mean amount of the bill she issues. Moreover, we have means of all different services provided by the physicians. These means are created from primary data set.

The physicians are paid according to the quantity of services they provide. Neither the quality of their work nor the cost structure of their practice is relevant for the price. This setting has the advantage that the physician has an incentive to lower her cost, but it has the disadvantage that quality does not pay. A high standard physician is likely to earn less than her colleague who is content with a lower standard.

The prices for all services are fixed in a fee schedule which is divided into 12 categories. Each category covers a specific medical topic and consists of their respective services, called $SERV\#$. A physician selling a service within a specific category is a (potential) supplier of the respective category. We build the variable $PSUPPLY$ by adding up the number of categories used by each physician. $PSUPPLY$ measures the variability of a physician's services. More than 500 different $SERV\#$s are part of the fee schedule. The variable $NUMB$ registers the number of different $SERV\#$ that a physician has invoiced during the year. Not surprisingly, $PSUPPLY$ and $NUMB$ are highly correlated.

Every single service has its price. Given the cost structure, the only possibility for a physician to increase her income is to expand the quantity of services. The more she sells, the more she earns. There are two ways to increase the number of services. First, a physician may sell additional services to her regular patients. Second, she may acquire new patients. As mentioned above, we neglect the latter possibility in our model, because physicians are not allowed to advertise in Switzerland.

Each physician invoices her services. The variable $BILLPP$ measures the number of bills per patient a physician issues in 1994. Physicians choose the billing dates. The more often they invoice, the higher the variable $BILLPP$. The variable $SERV1$ refers to the number of simple consultations per patient. $SERV1$ will be billed more frequently by physicians treating a lot of chronic patients. Consequently, $SERV1$ is a weak indicator for the extent of chronic diseases among the GP's patient population. It is only a weak indicator because a high $SERV1$-value can be reached independently of the patient population. Physicians may recommend additional check ups to their patients. The sum of all bills divided by the number of patients leads to the variable $TURNPP$. Accordingly, $TURNPP$ measures the turnover per patient of a physician.

4 Indicators for demand inducement

How can we distinguish physicians who induce demand from physicians who face a high realization of their (stochastic) demand? The first procedure is to examine the incentives for demand inducement. According to economic theory, incentives matter, i.e., if a physician has such an incentive for demand inducement, it will affect the market performance. As the theoretical model shows, idle capacities are a strong incentive to induce demand in order to generate additional income. The marginal cost of a service is zero whereas the price of it is strictly positive. The second procedure is to search directly for demand inducement.

The incentives for demand inducement are captured by two capacity indicators from our main data set: the number of patients n_i and a specific service named $SERV18$. The connection between capacities and the number of patients is obvious, provided the physicians are homogeneous in the sense of our model. The more patients a physician treats, the higher her expected utilization. $SERV18$ is invoiced if a session with a patient takes extra time which may happen in cases where a clear diagnosis cannot be obtained. $SERV18$ cannot be used, however, in combination with a diagnosis which involves medical devices. Therefore, $SERV18$ is invoiced for long diagnostic conversations. Economic reasoning suggests that a high $SERV18$ indicates free capacities. A physician who faces free capacities will rather keep her patients a bit longer in her practice than not doing anything and, as a consequence, not earning anything.

We consider the variables $NUMB$ and $BILLPP$ as direct indicators of demand inducement. The fee schedule described earlier is susceptible to be exploited. Physicians have a lot of discretion in using a specific service ($SERV\#$), because a treatment procedure is rarely well defined and may be split in different sets of services. Neither the patient nor the insurance company are able to control this splitting due to the lack of know-how in the former case and no possibility of monitoring in the latter case. Accordingly, to capture the extent to which the fee schedule is exploited, we use $NUMB$. The variable $NUMB$ shows a physician's degree of familiarity with the fee schedule, or to what extent she exploits the fee schedule. To control the variety of a physician's supply we use the variable $PSUPPLY$. A high value of $NUMB$ could also reflect a large variety of services supplied by the physician. $NUMB$ only indicates SID for similar values of $PSUPPLY$. The variable $BILLPP$ measures how important the money is for a physician. The higher $BILLPP$, the sooner a physician wants the money. Alternatively, $BILLPP$ can be interpreted as an indicator of income maximizing. In both cases, the hypothesis is that $BILLPP$ and SID go along. Table 1 lists the variables considered

-insert table 1 about here-

5 Comparing distributions

When comparing two physicians we need a method to judge the different frequencies of their services. Physician A, for example, invoices the service $SERV18$ 1.4 times on average while physician B has an average value of $SERV18$ which is 2.3. One major problem is that the reference distribution, which tells us the exact probability of a certain value given the optimal treatment, is unknown. Accordingly, we cannot tell whether the difference of 0.9 between A and B is large or negligible. The central limit theorem (CLT) helps us to answer this question. First, we formulate the CLT and then we show how to apply it to our question.[5]

If $x_1, ..., x_n$ are a random sample from any probability distribution with finite mean μ and finite variance σ^2 and $\overline{x}_n = (1/n) \sum_j x_j$, then

$$\sqrt{n} \left(\overline{x}_n - \mu_x \right) \xrightarrow{d} N \left[0, \sigma_x^2 \right]. \tag{1}$$

Consider a single service called $SERV\#$. Our data provide the mean numbers of the two physicians: $SERV\#_A$ and $SERV\#_B$. We do not know the reference distribution of $SERV\#$ but, as an approximation, we can use our primary data set and estimate the first and second moment of $SERV\#$. In this way we obtain $\widehat{\mu}$ and $\widehat{\sigma}$. Additionally, we know the number of patients that physician A and physician B have treated. This is all that is required to compare A and B. We compute for each physician $i = A, B$ the CLT-value which is defined as $CLTserv\#_i = \sqrt{N_i} \left(SERV\#_i - \widehat{\mu} \right) / \widehat{\sigma}$. According to the central limit theorem, $CLTserv\#_i$ is standard normally distributed. We are now able to apply these results to the question above. The difference of 0.9 between physician A and physician B is large, if the variance of $SERV\#$ is small and if the physician who deviates from zero more strongly also treats more patients. In this case the larger deviation cannot be explained by his small sample size. Consequently, the variable $CLTserv\#_i$ can be interpreted as the frequency of $SERV\#$ of physician i *relative* to the other physicians.

The following histogram shows the variable $CLTserv18$ for the 69 physicians who treated at least 20 patients.

- figure 2 about here -

Some values of $CLTserv18$ are considerably high. This is not surprising because they are not generated by a random sample but by physicians who react to incentives. Notice that the probability for a value larger than 1.96 is, according to equation (1), 2.5%, if we know exactly the first and second moment of the underlying distribution and if $n \to \infty$. These two conditions are, however, not fulfilled. Therefore, we need a random simulation in order to obtain an idea of a suitable confidence interval.

[5] See Greene (1993).

- figure 3 and 4 about here -

In comparing figure 2 with the two random samples of figures 3 and 4, it makes sense to define values of $CLTserv18$ larger than 4.2 as outliers. This threshold is justified by several simulations in which I estimated a kernel for different random samples. A value of 4.2 was always part of the 2.5% largest values in the sample. In using $CLTserv18$, we divide the physicians into two groups: those who have full capacities ($CLTserv18 < 4.2$) and those who have idle capacities ($CLTserv18 > 4.2$). Accordingly, $CLTserv18$ identifies the physicians with idle capacity. It turns out that 7 physicians have idle capacities. We then test the hypothesis that idle capacities lead to a high turnover per patient.

We define a high turnover per patient by the variable $CLTturnpp$, which is constructed applying equation (1) with $TURNPP$ as dependent variable. In figure 7 $CLTturnpp$ is shown for the 69 physicians.

- figure 5 about here -

We see that the distribution of $CLTturnpp$ is more symmetric than the one of $CLTserv18$. Values between -0.5 and 0.5 are the most frequent, however, there is a remarkable discrepancy of more than 11 between the highest and the lowest value. Accordingly, we conclude that although the physicians are all GPs they display a large variety in their turnover per patient. This finding suggests that random effects cannot explain the variety in the variable $TURNPP$.[6]

6 Results

In this section we present and test 4 hypotheses. At first, the correlation between idle capacities and turnover per patient is investigated (hypothesis 1). A positive correlation is interpreted as evidence in favor of SID. Furthermore, the validity of two crucial assumptions of our model presented in section 2 is tested: the homogeneity of the physicians and the homogeneity of their patient population. As an aspect of patients'

[6] See the sample statistics of the main data set in the appendix.

heterogeneity, we examine if their age may explain this positive correlation. In order to test the influence of physicians' heterogeneity (hypothesis 3) we run regressions for different levels of variety of supply measured by the variable $PSUPPLY$. Hypotheses 2 and 4 concerning the number of services used and the bills issued per patient respectively imply certain signs of the estimators in the regressions. Therefore, the regressions allow to test whether the estimators of these two direct indicators of SID display the predicted signs.

Hypothesis 1 *Physicians who have idle capacities show a turnover per patient above the average. Considering the number of patients n and the relative frequency of $SERV18$ as capacity indicators, we need to observe (a) a significant relationship between n and the relative turnover per patient ($CLTturnpp$) and (b) a significant difference in mean of $CLTturnpp$ and the two groups split by the value of $CLTserv18$.*

Figure 1 shows the positive relation between the number of patients and the average utilization of capacity. Investigating the effect of the number of patients as a continuous capacity indicator on the turnover per patient we obtain the following two tables:

$I = 69$	n	$TURNPP$
n	1	$-0.24(p = 0.043)$
$TURNPP$	$-0.24(p = 0.043)$	1

Table 2: Pearson Correlation coefficient of the number of patients and the turnover per patient

$I = 69$	n	$CLTturnpp$
n	1	$-0.28(p = 0.021)$
$CLTturnpp$	$-0.28(p = 0.021)$	1

Table 3: Pearson Correlation coefficient of the number of patients and the *relative* turnover per patient

There is a negative mutual relationship between (i) turnover per patient and number of patients (table 2) and (ii) turnover per patient relative to the other GPs versus number of patients (table 3). The correlation of (ii) has a lower p-value than the one in (i). This higher significance makes sense since the CLT-transformation corrects random effects.[7] The age of the patient population does not explain this result, as the

[7] The correlation of the groups separated by X-ray machine leads to similar results: -0.35(0.032)/-0.37(0.024) for the GPs with X-ray and -0.30(0.105)/-0.45(0.011) for GPs without X-ray. The random effect is stronger for the GPs without X-ray because their number of patients is lower on the average.

mean of the age is not correlated with the number of patients.[8] Accordingly, Hypothesis 1 cannot be rejected.

In order to test Hypothesis 1 concerning the discrete capacity indicator, two groups are built according to their value of $CLTserv18$. Beyond a threshold value of 4.2 physicians are assumed to have idle capacities. We compare the means of $CLTturnpp$ of the two groups and perform a t-test.[9]

capacity	I	mean	standard deviation	t-test
idle	7	1.98	2.91	H_0 : means are the same
full	62	0.01	2.33	t-value= $2.06 (p = 0.043)$

Table 4: Mean comparison of the variable $CLTturnpp$

capacity	I	mean	standard deviation	t-test
idle	7	1.63	2.96	H_0 : means are the same
full	62	0.04	2.34	t-value= $1.66 (p = 0.101)$

Table 5: Mean comparison of the variable $CLTturnex18$

From table 4 we see a significant difference in $CLTturnpp$ for the two groups. The group with full capacities shows nearly the expected mean value of zero, whereas the group with idle capacities displays a mean of 1.98. Although $SERV18$ only contributes 0.9% to the turnover per patient on the average we refer to the variable $CLTturnex18$, which does not include $SERV18$, in order to guarantee for the independence between $TURNPP$ and $SERV18$.[10] Table 5 shows the mean comparison of the variable $CLTturnex18$ between the two groups. At a 95% significance level the null hypothesis of equal means cannot be rejected.

Up to now we regard $SERV18$ as a capacity indicator for all physicians. As stated earlier $SERV18$ is invoiced without any technical devices, i.e., it is forbidden to invoice $SERV18$ in combination with X-ray pictures. As a result, physicians with an X-ray

[8] We find a positive correlation between the standard deviation of the patient population's age ($SAGE$) and the number of patients. The relationships between $TURNPP$ and $SAGE$ and the one between $CLTturnpp$ and $SAGE$ are, however, not significant.

[9] The underlying assumptions of this test is that the variables are normally and independently distributed with equal variances within each group. In the appendix we show that the former and the latter are fulfilled (table 13 and table 14). With regard to the assumption of independence see footnote 3.

[10] There are, however, much more important services. $SERV1$, for example, contributes 26.4% to the turnover per patient on the average.

machine in their practice do not use $SERV18$ as often as their colleagues without this device. They have, however, other possibilities to increase their utilization in case of idle capacities. Therefore, $SERV18$ is a better capacity indicator for those physicians without these medical devices. We perform the same t-test as above for the physicians without an X-ray machine. It is not possible to perform this test for the other group, because there is only one physician with an X-ray machine who has idle capacities according to $SERV18$.

capacity	I	mean	standard deviation	t-test
idle	6	2.09	3.12	H_0 : means are the same
full	25	-0.90	2.01	t-value= $2.92 (p = 0.007)$

Table 6: Mean comparison of the variable $CLTturnpp$; physicians without X-ray machine

capacity	I	mean	standard deviation	t-test
idle	6	1.73	3.24	H_0 : means are the same
full	25	-0.88	2.00	t-value= $2.54 (p = 0.017)$

Table 7: Mean comparison of the variable $CLTturnex18$; physicians without X-ray machine

Both variables, $CLTturnpp$ and $CLTturnex18$, display a significant discrepancy in mean for the two groups. The difference in the latter variable implies not only that physicians with idle capacities diagnose too much but also that they sell services in excess for therapy reasons. As table 5 shows, this does not hold true for all physicians.

The results from tables 4 to 7 may be interpreted in two different ways. On the one hand, it is possible to conclude that the GPs with X-ray machines work on their capacity constraint (there is only one exception) whereas 20% of their colleagues without this machine have idle capacities. On the other hand, one may argue that $SERV18$ is a bad capacity indicator for GPs with X-ray and, therefore, we find only one GP with idle capacities. This latter interpretation is supported by the fact that the X-ray group use $SERV18$ significantly less than the GPs without X-ray. Furthermore, the X-ray group is likely to be equipped with other technical devices which may be exploited in order to fill idle capacities. The comparison of the two capacity indicators gives further evidence of the latter interpretation. The number of patients per physician and the variable $SERV18$ do not correlate for all physicians. Nevertheless, if we only consider physicians without an X-ray machine we can reveal a significant relationship. A t-test rejects the null hypothesis of equal means with a p-value of 0.02.

Another t-test is performed to ensure that the variety of supply does not drive the result. Table 16 in the appendix shows that the variable $PSUPPLY$ is not significantly different for the two groups with idle and full capacities respectively. Furthermore, the same test is applied to the mean and the standard deviation of the patient population's age. No connection is found between age of the patients and capacity measured by $SERV18$. Accordingly, the result cannot be explained by the differences of the patient population in terms of their age.

Regressions

In order to test the homogeneity of the physicians under consideration, I perform several regressions. In addition, these regressions allow to test the direct SID indicators, namely $NUMB$ and $BILLPP$. Furthermore, we explain the turnover per patient using non-medical variables. In what follows, we assume a Cobb-Douglas relationship between turnover per patient and the explaining variables, e.g., number of patients and number of services used. In contrast to a linear relationship, the Cobb-Douglas relationship allows for variable marginal effects. The effect of $NUMB$ on $TURNPP$ is, for example, likely to be diminishing. A certain amount of $NUMB$ suffices to induce demand. The elbowroom for choosing a menu of services is then large enough. Beyond this amount $NUMB$ becomes a weaker indicator for SID.[11] To control for the variety of the services supplied, $PSUPPLY$ is included. This leads to the following equation

$$TURNPP_i = C \cdot NUMB_i^{\alpha} \cdot n_i^{\beta} \cdot PSUPPLY_i^{\varepsilon} \qquad (2)$$

Hypothesis 2 *Physicians who know the fee schedule particularly well display a higher turnover per patient. Consequently, we will observe a positive and significant sign of* $\widehat{\alpha}$.

The more services a physician uses, the more familiar she is with the fee schedule and the better she is able to exploit the fee schedule. This should have a positive effect

[11] A seperate regression is shown in table 17 (appendix). No significant relationship between $TURNPP$ and $NUMB$ is found for physicians with a value of $NUMB$ higher than 48.

on the turnover per patient. Furthermore, the coefficient $\widehat{\varepsilon}$ should also be positive, as the same effect is expected for a larger variety of services. A physician who supplies potentially more services performs a higher turnover per patient regardless whether she induces demand or not. The negative sign of $\widehat{\beta}$ follows from table 2.

In order to estimate equation (2) we take the natural logarithm. Consequently, the coefficient estimates can be interpreted as elasticities.

$$\ln(TURNPP_i) = c + \alpha \ln(NUMB_i) + \beta \ln(n_i) + \varepsilon \ln(PSUPPLY_i) + v_i$$

I	$\widehat{c}$	$\widehat{\alpha}$	$\widehat{\beta}$	$\widehat{\varepsilon}$	White Test
69	3.48 (12.78)	0.73 (5.63)	-0.31 (-5.87)	-0.46 (-2.60)	10.71 ($\chi^2(9)$)
69	3.28 (11.76)	0.50 (5.41)	-0.29 (-5.31)	$\varepsilon \equiv 0$	3.86 ($\chi^2(5)$)
69	3.96 (13.15)	$\alpha \equiv 0$	-0.18 (-3.50)	0.32 (2.22)	6.91 ($\chi^2(5)$)

Table 8: GLS estimates for $NUMB$, n and $PSUPPLY$; t-values in parentheses.

Table 8 displays the estimates of three GLS regressions.[12] Since the estimate of α is significantly positive in the first and the second estimation, hypothesis 2 cannot be rejected. The estimates in the first row can be read as follows. As the number of billed services increases by 10%, for instance, the turnover per patient increases by 7.3% on the average. In contrast, if a physician has 10% more patients than her colleague, she will exhibit a turnover per patient which is 3.1% lower on the average. These two observations confirm hypotheses 1 and 2 respectively. There is one surprising result concerning the negative value of $\widehat{\varepsilon}$ in the first estimation. Although $\widehat{\varepsilon}$ is, as expected, positive in the third estimation, the sign changes as $NUMB$ is included in the regression. In addition, as $PSUPPLY$ and $NUMB$ are positively correlated, one would expect that $PSUPPLY$ lowers the effect of $NUMB$ on $TURNPP$.[13] We observe, however, the contrary. This enforces the interpretation of $NUMB$ as an indicator of fee schedule exploiting rather than as an indicator of the variety of services. A physician who treats her patients in more specialities does not show a higher turnover per patient. The positive sign of $\widehat{\varepsilon}$ in the third estimation is due to the high correlation of $PSUPPLY$ and $NUMB$.

[12] Whenever heteroscedasticity is present, the GLS estimator is used.

[13] The Pearson correlation coefficient is 0.78 and highly significant.

In our model, we assume for homogeneous physicians. Accordingly, we have to analyze whether this assumption is legitimate for our SID results. Therefore, we formulate the following hypothesis.

Hypothesis 3 *The physicians are homogeneous, i.e., there are no structural differences concerning their supply. Consequently, no differences of the estimator vector for several regressions using similar values of $PSUPPLY$ need to be observed.*

We perform several regressions with $\varepsilon \equiv 0$ in which the population of the GPs under consideration is split according to $PSUPPLY$. In addition, we differentiate between the physicians with an X-ray and those without. The coefficient estimates are shown in table 18 in the appendix. The same signs of the coefficients as in table 8 are observed for all estimates. Hypothesis 3 is tested by an F-test. The vector of estimates is equal for all groups under the null hypothesis.[14]

$$\ln(TURNPP_i) = c + \alpha \ln(NUMB_i) + \beta \ln(n_i) + \upsilon_i$$

first group	second group	F-statistik
$PSUPPLY > 9$	$PSUPPLY < 10$	F(3,63)=0.48
$PSUPPLY > 8$	$PSUPPLY < 9$	F(3,63)=1.05
$PSUPPLY > 7$	$PSUPPLY < 8$	F(3,63)=1.48
$PSUPPLY > 6$	$PSUPPLY < 7$	F(3,63)=2.10
with X-ray	without X-ray	F(3,63)=0.66

Table 9: Chow test for two groups.

As table 9 shows, the null hypothesis of an equal parameter vector for all regressions cannot be rejected. The same coefficient vector for all subgroups implies that the heterogeneity of the physicians does not drive our results. This supports the assumption of homogeneity among the physicians, i.e., differences in their supply are not crucial.

As an extension consider the following equation

$$TURNPP_i = C \cdot NUMB_i^{\alpha} \cdot n_i^{\beta} \cdot BILLPP^{\gamma} \cdot SERV1^{\delta}. \tag{3}$$

We expect a positive sign of $\widehat{\delta}$ because $SERV1$ is a substantial part of the turnover per patient (see footnote 10), and, as mentioned earlier, $SERV1$ is an indicator for

[14] A Chow test for three groups is shown in table 20 in the appendix.

long-term patients who cause a higher turnover per patient. The expected sign of $\widehat{\gamma}$ is ex ante not clear. On the one hand, we would expect a negative sign. A physician who does not induce demand (i.e. has a low $TURNPP$) faces a narrow total account and, therefore, needs to invoice the bills sooner. On the other hand, a positive sign of $\widehat{\gamma}$ is conceivable. A high value of $BILLPP$ is interpreted as an indicator of income maximizing that may go along with demand inducement. The following hypothesis supports the latter interpretation.

Hypothesis 4 *A physician who invoices the bills sooner, displays a higher turnover per patient. Accordingly, a positive and significant estimate for γ should be observed.*

$$\ln(TURNPP_i) = c + \alpha \ln(NUMB_i) + \beta \ln(n_i) + \gamma \ln(BILLPP_i) + \delta \ln(SERV1_i) + v_i$$

I	$\widehat{c}$	$\widehat{\alpha}$	$\widehat{\beta}$	$\widehat{\gamma}$	$\widehat{\delta}$	$R^2(adj.R^2)$
69	3.54	0.22	-0.19	1.22	0.11	0.47
	(14.13)	(2.55)	(-3.49)	(3.66)	(1.37)	(0.44)

Table 10: OLS estimates for $NUMB$, n, $BILLPP$ and $SERV1$; t-values in parentheses.

Table 10 confirms the findings of table 8.[15] Furthermore, we obtain a significant *positive* sign of $BILLPP$ which supports Hypothesis 4. All the more because $SERV1$ is also part of the regression and controls for the population of the patients, i.e., for the long-term patients in particular. Dropping out $SERV1$ and using the Generalize Least Square estimator leads to the results in table 11.

$$\ln(TURNPP_i) = c + \alpha \ln(NUMB_i) + \beta \ln(n_i) + \gamma \ln(BILLPP_i) + v_i$$

I	$\widehat{c}$	$\widehat{\alpha}$	$\widehat{\beta}$	$\widehat{\gamma}$	White Test
69	3.40 (13.69)	0.28 (2.86)	-0.18 (-3.39)	1.28 (4.40)	8.12 ($\chi^2(9)$)

Table 11: GLS estimates for $NUMB$, n and $BILLPP$; t-values in parentheses.

As before, the coefficient estimates can be read as elasticities. For $\widehat{\gamma}$ we observe a coefficient value greater than 1 in absolute value. Therefore, the effect of $BILLPP$ on $TURNPP$ is more than proportional. A 10% increase in the number of bills per

[15] When we use White's consistent covariance estimator under the hypothesis of heteroscedasticity we obtain a t-value of 3.86 for $\widehat{\gamma}$ and a t-value of 0.67 for $\widehat{\delta}$.

patient, for example, leads to a 12.8% increase in the turnover per patient. In contrast, the estimates $\widehat{\alpha}$ and $\widehat{\beta}$ are lower than 1 in absolute value. Accordingly, the marginal effects of $NUMB$ and n on $TURNPP$ are, as expected, diminishing.

7 Conclusions

We present a model to describe the physicians' behavior highlighting the importance of capacity utilization. Our empirical findings cannot reject the hypotheses generated by the model, i.e., physicians whose capacity indicators suggest idle capacities show a higher turnover per patient. This result gives evidence of SID. It raises the natural question whether the assumptions of the model fit with the data. Let us go through the main objections.

• **Homogeneity of the physicians**

All physicians are general practitioners and work in the city of Basle. They differ, however, as to whether they have an X-ray machine in their practice or not. This dichotomy is important for services involving this device. We saw this earlier with regard to the interpretation of $SERV18$. It is, however, not important with respect to their potential supply (excluding X-ray pictures). A patient does not choose a GP according to the criterion of an X-ray machine. In a city like Basle it is not costly to take an X-ray picture with another GP as the distances are minor. The Chow tests confirm this conjecture.

As an indicator of heterogeneity we propose the variable $PSUPPLY$ reflecting the actual variety of services. X-ray pictures are one category of services among others (see section 3). The regressions for subgroups built by $PSUPPLY$ suggest no heterogeneity. Moreover, there is no relationship between capacity and $PSUPPLY$. Concluding, heterogeneity of the physician does not drive the results.

• **Homogeneity of the patient population**

All patients live near Basle since their GP should be in the vicinity. From a medical point of view they do not differ substantially, because patients with chronic diseases led to obtain their treatment from specialists. In addition, everybody has her GP, so the potential clients of the GPs are the whole population. If somebody has a health problem, she decides to see a GP. This process is exogenously given for each GP. As mentioned in the former section, the heterogeneity of the patients with regard to their age does not generate our results.

We cannot, however, exclude the possibility that the physicians themselves initiate a selection among the patients. Two cases are conceivable. First, suppose a high quality physician who is not allowed to charge higher fees due to the price controls. Nevertheless, her high quality standard may attract patients with more complicated health problems, or she may not delegate her patients to specialists so often. As a consequence, this physician achieves a higher turnover per patient. Second, a physician may prescribe too generously. As a result, she may attract hypochondriacs who wish a treatment for every slightest health disturbance. Again, the physician obtains a high turnover per patient. In the first case, the selection arises from medical differences among physicians and is unrelated to SID. The second case, however, fits our definition of SID. Therefore, we have to deal carefully with the first case in order to justify our results. The strength of this selection depends on the number of other GPs nearby and the number of specialists around. More GPs allow a higher selection, because the patients have a greater choice. On the contrary, more specialists damp the effect since they absorb the difficult cases from the GPs. In our data these two effects move in opposite directions, because about 100 GPs and about 700 specialists work in Basle. It is, however, not clear if 7 specialists per GP are enough to neglect this selection problem. Unfortunately, this is not testable with the data at hand.

- **Omitted variables**

  Patients' characteristics

  With the help of patients' characteristics such as age, body mass index, smoking habits, education, profession, income, etc., we could test the selection problem mentioned in the previous paragraph. In addition, these characteristics could give further insights into the existence and the features of SID. Nevertheless, we think that the availability of these data would not change our findings.

  Age of the physicians

  The data do not contain any information concerning the age of the physicians. But it is not clear in advance how age may affect the turnover. Different hypotheses are possible: first, a younger physician issues higher bills due to her higher technical standard (e.g. new methods) or because she is more risk averse than her older colleagues.

Second, a younger GP has a lower turnover because she does not know the fee schedule as well as a more experienced colleague.[16]

Specification of the physician's practice

If we had data on the specification of the practice, e.g., set-up and financial encumbrance, we would be able to test hypotheses concerning the importance of economic factors. A significant relationship between turnover per patient and these specifications would provide further evidence of SID. This information would give further insights into the causes of SID although the results at hand still remain valid.

- **Validity of the indicators**

The lack of additional data forces us to use indicators in order to test our hypotheses. The extra time service ($SERV18$) and the number of patients treated (n) are capacity indicators which are far from being perfect. The same is true for the number of services used ($NUMB$) and the number of bills issued per patient ($BILPP$) as SID indicators. Nevertheless, hypotheses 1, 2 and 3 cannot be rejected. Moreover, the findings are consistent with the model.

- **Causality**

There is a causality problem in every cross section analysis. Our empirical results are, however, consistent with our theoretical model. Furthermore, we show that the underlying assumptions are plausible and fit the data. Naturally, one can find causality-reversed interpretations of the empirical results. A time series analysis would give further insights.

Our main policy implication is that the Swiss government should reduce the number of study places leading to a degree in medicine. As we have shown, the physicians can fill their idle capacities to their advantage. Since they are in the fortunate position to open their own practice anytime, physicians will never be unemployed and have a strong incentive to induce demand. As the number of physicians rises more than the actual demand, idle capacities become more likely. In Switzerland, discussions suggesting limiting study places for medicine students have started. At the University of Zurich, the biggest university in Switzerland, numerus clausus for medicine students is already introduced. It is expected that the other universities will follow.

[16]These arguments were privately communicated by a representative of the insurance company.

An alternative suggestion might be to limit directly the number of practices by auctioning a certain number of licences for running a practice. As the optimal number of practices is not known, however, this approach exhibits an information problem. Nevertheless, the direction of policy seems to be clear: our empirical findings suggest that too many physicians are working in the city of Basle today.

A last policy implication concerns the compensation schedule. A different compensation schedule for the physicians could weaken the incentive to sell services for non-medical reasons. A useful tool to design such a fee schedule is the 'equal compensation principle' ensuring that there exists no economic incentive for the physician to prefer certain services.[17] According to this principle, all services offered should give the same marginal rate of return to the physician. As a result, the physicians allocate their time, attention, and effort correctly among the various activities to be done. Health Maintenance Organizations (HMO), an application of this principle, are even able to eliminate the incentive for selling too many services.[18] Therefore, in Switzerland this insurance set-up deserves a greater attention than the currently market share of less than 1% suggests.

[17] see Milgrom & Roberts (1992)

[18] The common criticism against HMO's concerning their lower quality standard could not be confirmed by a recent study. See BSV (Bundesamt für Sozialversicherung) (1998).

8 Appendix

8.1 Sample Statistics

8.1.1 Primary data set

Variable	n	mean	standard deviation	miminum	maximum
$SERV1$	8544	2.87	2.69	0	35
$SERV18$	8544	0.06	0.36	0	8
$TURNPP$	8544	43.43	55.06	0	3327
$TURNEX18$	8544	43.04	54.73	0	3327

Table 12: Sample statisic of the basic data set

8.1.2 Main data set[19]

Variable	n	mean	standard deviation	minimum	maximum
$SERV1$	69	3.02	1.20	0.68	8.26
$CLTserv18$	69	0.41	3.51	-3.86	16.17
$TURNPP$	69	46.14	16.24	5	75
$TURNEX18$	69	43.00	10.33	9	75
$CLTturnpp$	69	0.21	2.45	-4.37	6.70
$CLTturnex18$	69	0.22	2.46	-4.34	7.78
$NUMB$	37	51.35	13.77	9	75
$NUMB$	69	42.68	16.43	5	75
$PSUPPLY$	69	7.75	1.93	2	11
$BILLPP$	69	1.19	0.13	1	1.7
n	69	122.72	89.31	21	504

Table 13: Sample statistic of the main data set

[19] 69 physicians have at least 20 patients and 37 physicians have more than 100 patients

8.2 Tests

Variable	I	Physicians considered	capacity	W-statistic
$CLTturnpp$	62	all	full	$0.97(p = 0.37)$
$CLTturnpp$	7	all	idle	$0.89\ (p = 0.27)$
$CLTturnex18$	62	all	full	$0.97(p = 0.34)$
$CLTturnex18$	7	all	idle	$0.91(p = 0.41)$
$CLTturnpp$	25	without X-ray machine	full	$0.94(p = 0.15)$
$CLTturnpp$	6	without X-ray machine	idle	$0.86(p = 0.18)$
$CLTturnex18$	25	without X-ray machine	full	$0.93(p = 0.11)$
$CLTturnex18$	6	without X-ray machine	idle	$0.88(p = 0.27)$

Table 14: Normality tests by Shapiro & Wilk (1965)

Variable	I	Physicians considered	capacity	F-statistic (degrees of freedom)
$CLTturnpp$	62	all	full	1.55 (6,61)
$CLTturnpp$	7	all	idle	$p = 0.355$
$CLTturnex18$	62	all	full	1.60 (6,61)
$CLTturnex18$	7	all	idle	$p = 0.325$
$CLTturnpp$	25	without X-ray machine	full	2.49 (5,24)
$CLTturnpp$	6	without X-ray machine	idle	$p = 0.120$
$CLTturnex18$	25	without X-ray machine	full	2.62 (5,24)
$CLTturnex18$	6	without X-ray machine	idle	$p = 0.100$

Table 15: Tests for equal variances, $CLTturnpp$ and $CLTturnex18$

capacity	I	mean	standard deviation	t-test
idle	7	7.14	1.35	H_0 : means are the same
full	62	7.82	1.98	$t - value = -0.88(p = 0.3806)$

Table 16: Mean comparison of the variable $PSUPPLY$

8.3 Regressions

$\ln(TURNPP_i) = c + \alpha \ln(NUMB_i) + \beta \ln(n_i) + \gamma \ln(BILLPP_i) + \delta \ln(SERV1_i) + \nu_i$							
Type	I	$\widehat{c}$	$\widehat{\alpha}$	$\widehat{\beta}$	$\widehat{\gamma}$	$\widehat{\delta}$	$R^2(adj.R^2)$
OLS	69	3.37 (35.95)	$\alpha \equiv 0$	$\beta \equiv 0$	1.62 (5.18)	0.13 (1.46)	0.37 (0.35)
OLS	69	3.54 (14.13)	0.22 (2.55)	-0.19 (-4.49)	1.22 (3.66)	0.11 (1.37)	0.47 (0.44)
OLS	69	3.68 (16.03)	0.21 (2.45)	-0.20 (-3.56)	1.37 (4.29)	$\delta \equiv 0$	0.45 (0.43)

Table 17: OLS regressions

$\ln(TURNPP_i) = c + \alpha\ln(NUMB_i) + \beta\ln(n_i) + \gamma\ln(BILLPP_i) + \upsilon_i$						
Type	I	$\widehat{c}$	$\widehat{\alpha}$	$\widehat{\beta}$	$\widehat{\gamma}$	White Test
OLS	25	3.28 (3.63)	0.30 (1.23)	-0.17 (1.92)	1.24 (3.17)	7.90($\chi^2(9)$)

Table 18: OLS regrssion for physicians with $NUMB$>48

$\ln(TURNPP_i) = c + \alpha\ln(NUMB_i) + \beta\ln(n_i) + \gamma\ln(BILLPP_i) + \upsilon_i$						
Type	$PSUPPLY$	I	$\widehat{c}$	$\widehat{\alpha}$	$\widehat{\beta}$	$R^2(R^2adj.)$
GLS	whole range	69	3.28(11.76)	0.50 (5.41)	-0.29(-5.31)	
OLS	>9	11	2.11 (2.93)	0.69 (2.90)	-0.22 (-2.15)	0.51 (0.39)
OLS	>8	29	1.86 (3.05)	0.83 (4.63)	-0.27 (-4.57)	0.52 (0.48)
OLS	>7	43	2.29 (5.10)	0.74 (5.36)	-0.29 (-4.87)	0.46 (0.48)
GLS	>6	54	2.53 (6.66)	0.69 (5.90)	-0.29 (-5.30)	
OLS	9/10	27	1.77 (2.46)	0.85 (4.05)	-0.28 (-4.37)	0.49 (0.45)
OLS	9	18	1.59 (1.55)	0.95 (3.25)	-0.32 (-3.58)	0.51 (0.45)
OLS	8/9	32	2.21 (3.93)	0.83 (4.49)	-0.34 (-4.30)	0.45 (0.41)
OLS	8	14	1.78 (1.84)	1.05 (2.88)	-0.41 (-2.76)	0.46 (0.36)
GLS	7/8	25	2.08 (3.18)	0.95 (3.70)	-0.40 (-3.56)	
OLS	6/7	16	2.35 (2.56)	1.00 (3.08)	-0.49 (-3.44)	0.51 (0.43)
OLS	5/6/7	21	3.35 (2.56)	0.54 (2.90)	-0.35 (-3.16)	0.40 (0.34)
OLS	4/5/6/7	24	3.66 (6.12)	0.48 (2.36)	-0.36 (-3.10)	0.33 (0.27)
OLS	<9	40	3.77 (9.87)	0.37 (2.96)	-0.30 (-3.52)	0.27 (0.23)
OLS	<8	26	4.03 (7.67)	0.32 (2.11)	-0.32 (-2.87)	0.29 (0.23)
OLS	<7	15	4.85 (4.86)	0.17 (0.87)	-0.42 (-2.10)	0.31 (0.19)
OLS	X-ray	38	4.04 (7.05)	0.27 (1.46)	-0.26 (3.20)	0.23 (0.19)
OLS	no X-ray	31	3.82 (8.93)	-0.30 (-3.25)	0.35 (2.92)	0.32 (0.28)

Table 19: Regressions for subgroups

$\ln(TURNPP_i) = c + \alpha\ln(NUMB_i) + \beta\ln(n_i) + \upsilon_i$			
first group	second group	third group	F-statistik
$PSUPPLY > 9$	$PSUPPLY = 9$	$PSUPPLY < 9$	F(3,60)=1.22
$PSUPPLY > 9$	$PSUPPLY = 8,9$	$PSUPPLY < 8$	F(3,60)=1.78
$PSUPPLY > 9$	$PSUPPLY = 7,8,9$	$PSUPPLY < 7$	F(3,60)=2.65
$PSUPPLY > 8$	$PSUPPLY = 8$	$PSUPPLY < 8$	F(3,60)=2.04
$PSUPPLY > 8$	$PSUPPLY = 7,8$	$PSUPPLY < 7$	F(3,60)=3.31
$PSUPPLY > 7$	$PSUPPLY = 7$	$PSUPPLY < 7$	F(3,60)=2.71

Table 20: Chow test for three groups

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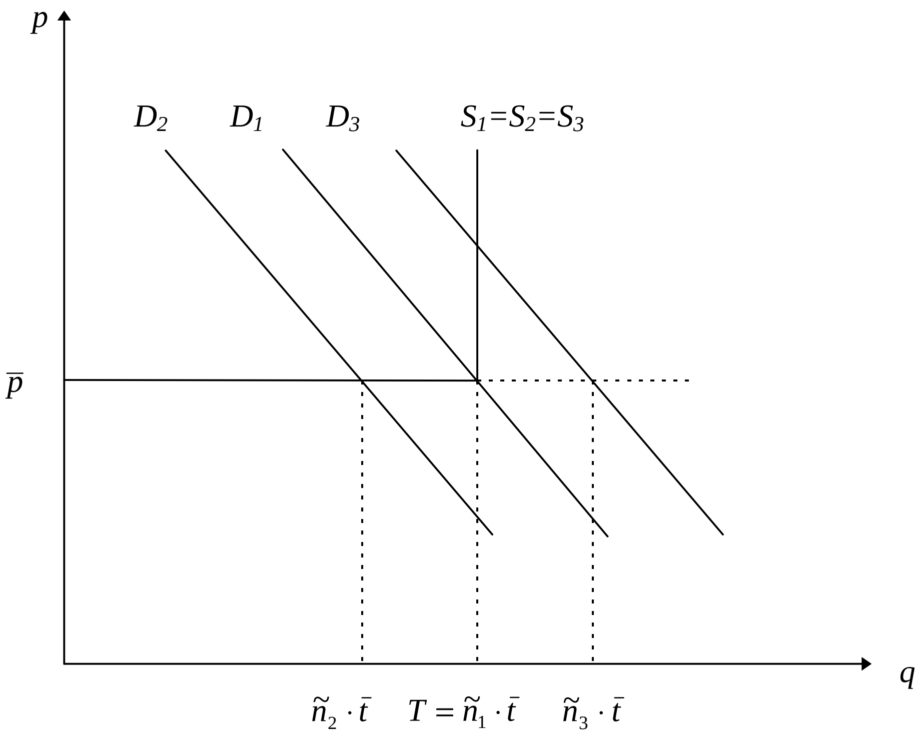

Figure 1: Physician 1 faces just enough patients and chooses $n_1 = \tilde{n}_1$ and $d_1 = 0$.
Physician 2 faces too few patients and chooses $n_2 = \tilde{n}_2$ and $d_2 = T / n_2 - \bar{t}$.
Physician 3 faces too many patients and chooses $n_3 = T / \bar{t}$ and $d_3 = 0$.

name	**defined as**	**indicator for (if high value)**
$SERV\#$	service number #	-
$SERV1$	normal consultation per patient	many chronic patients
$SERV18$	extra time within a consultation per patient	idle capacity
$TURNPP$	turnover per patient	SID or particularly sick patients
$TURNEX18$	turnover per patient excluding $SERV18$	SID or particularly sick patients
n	number of patients treated	full capacity
$NUMB$	number of different services used	exploiting the fee schedule
$PSUPPLY$	number of different categories of services used	variety of services supplied
$BILLPP$	number of bills issued per patient	importance of money

Table 1: List of variables

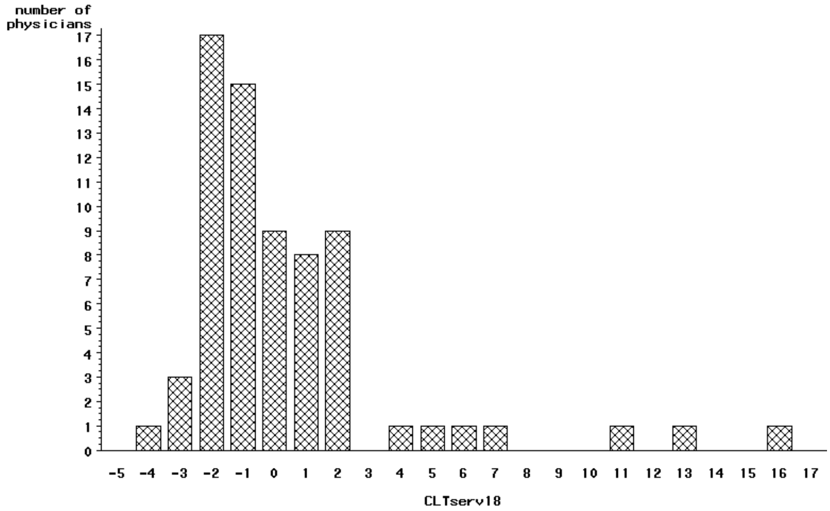

Figure 2: 69 physicians with at least 20 patients, $CLTserv18$.

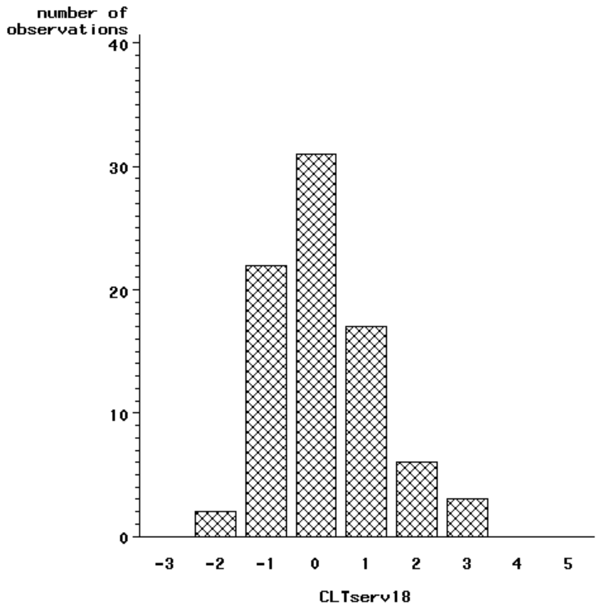

Figure 3: Random sample 81 times 122 patients, $CLTserv18$.

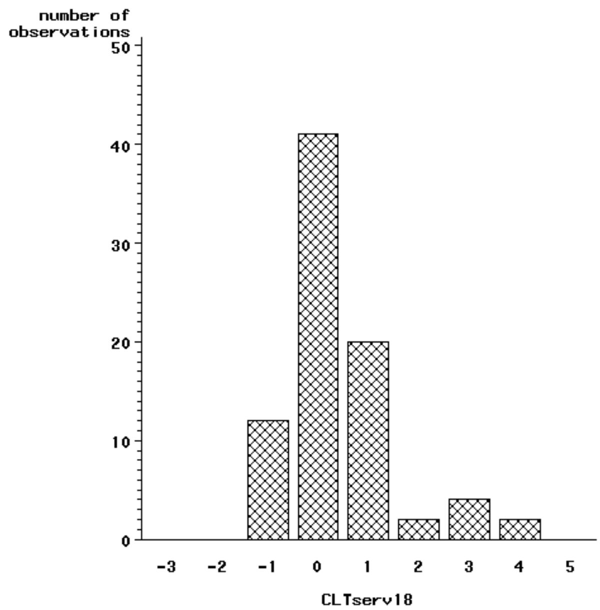

Figure 4: Random sample 81 times 35 patients, $CLTserv18$.

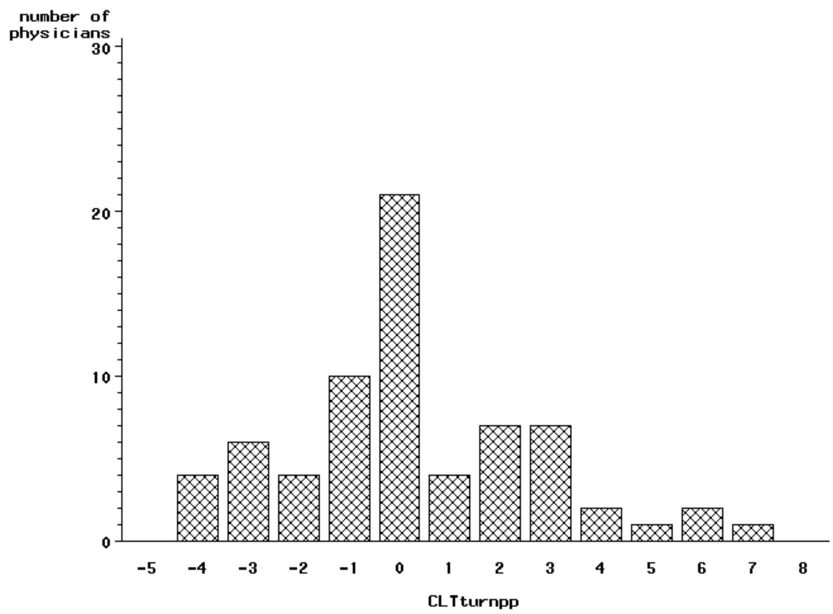

Figure 5: Relative turnover per patient, $CLTturnpp$.