Dispensing practices and antibiotic use

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Abstract

The regulation on prescribing and dispensing of antibiotics has a double purpose: to enhance access to antibiotic treatment and to reduce the inappropriate use of drugs. Nevertheless, incentives to dispensing physicians may lead to inefficiencies. We sketch a theoretical model of the market for antibiotic treatment and empirically investigate the impact of self-dispensing on the per capita outpatient antibiotic consumption using data from small geographic areas in Switzerland. We find evidence that a greater proportion of dispensing practices is associated with higher levels of antibiotic use. This suggests that health authorities have a margin to adjust economic incentives on dispensing practices in order to reduce antibiotic misuse.

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1 Introduction

Prescribing and dispensing of drugs are main aspects of access to primary health care. Dispensing has been physicians’ responsibility for long time. Nowadays, in developed countries physicians’ main role is to prescribe drugs without direct dispensing (Trap, 1997).\(^1\) The reason is two-fold. First, the need to avoid a conflict of interest for the prescriber, and second, to optimise rationality of treatment by ensuring good practice in dispensing (Trap and Hansen, 2003). The latter explanation recalls the fact that pharmacists can often review doctors’ prescriptions and check contraindications and drug interactions.

However, direct dispensing of drugs is generally possible in some countries, likely for the purpose of improving access to pharmaceuticals. For instance, one Scottish region (Highland) included almost 20% of the total number of dispensing doctors in Scotland in 2005 (Information Services Division of the National Health System in Scotland, 2006). In Switzerland, physicians are allowed to sell drugs directly to their patients in most cantons, with few exceptions.\(^2\) The reason may not lie straightforwardly in the regulator’s objective to compensate for the lack of access to drug treatment. Historical and cultural aspects may have contributed to shape different rules across the country. Consequently, the low density of pharmacies in one area may either be the reason that led the regulator to allow for self-dispensing or the consequence of the advantage of dispensing practices in comparison to pharmacies. The proportion of dispensing practices among all practices is highly heterogeneous across the country and is only slightly correlated with the degree of urbanization.\(^3\)

The purpose of this article is to explore the role of practice regulation in enhancing access to antibiotic treatment and reducing inappropriate use of antibiotics. It has been suggested that the regulatory policy that allows physicians to sell drugs directly to the patient may unintentionally promote the overuse of drugs (Holloway, 2005; Nelson, 1987). A question arises as to whether the regulator underestimates the

\(^1\)For instance, doctors are not allowed to sell drugs directly to their patients in Germany and the Scandinavian region.

\(^2\)Switzerland is a federal state made of 26 cantons with remarkable differences in terms of organization of the health care system and health care policy. Self-dispensing is not allowed in Geneva, Vaud, Balle ville, Ticino and Argau.

\(^3\)The Swiss territory can be divided into 240 small areas, each of them with at least four pharmacies, drugstores or dispensing practices. The coefficient of correlation between the proportion of dispensing doctors and the density of the population was -0.27 in 2002. The correlation with the density of pharmacies was -0.36.
potential inefficiencies induced by incentives on dispensing practices.

The literature lacks theoretical analysis of self-dispensing and empirical investigations generally use a correlation coefficient approach rather than applying econometric models. There is evidence that prescribing costs per patient in dispensing practices are higher than costs in non-dispensing practices. This may be explained by reluctance to prescribe generics (Morton-Jones and Pringle, 1993). Moreover, dispensing doctors charge higher retail prices (Abood, 1989). Finally, they have a tendency to prescribe more drugs per capita in comparison with non-dispensing practices (Trap et al., 2002). This seems to be particularly evident for antibacterials. Focusing on one antibiotic substance (cotrimoxazole), Trap and Hansen (2002) examined differences in the rationality of the prescription in relation to diagnosis and symptoms between dispensing and non-dispensing doctors. Dispensing doctors were found to prescribe an antibiotic 2.5 times more frequently than other doctors. As a consequence, dispensing practices may lead to increasing health hazards and bacterial resistance.

In this article we propose a theoretical model of the market for community antibiotic treatment. Under a fee-for-service remuneration scheme as in Switzerland, doctors receive a consultation fee which varies with time allocated to the patient and the diagnostic tests performed. Dispensing doctors may incur additional costs for drugs in stock and gain a margin on antibiotics sold to the patient. We argue that the interaction between imperfect information on the nature of patient’s infection and economic incentives to dispensing practices may increase the likelihood of antibiotic prescriptions, *ceteris paribus*.

We then investigate the impact of dispensing practices on the individual outpatient antibiotic consumption empirically, using data from small geographical areas in Switzerland. The effect of dispensing practices is disentangled by means of econometric estimations which take into account the main demand-side and supply-side determinants of antibiotic use.

The article is organized as follows. In Section 2 we sketch the model and derive the equilibrium levels of antibiotic use for dispensing and non-dispensing practices. Section 3 empirically investigates the impact of dispensing practices on antibiotic use and discusses the results. Section 4 concludes.
2 A model of markets for antiinfective treatment

In the market for primary care there are $N$ individuals uniformly distributed along a circle line. We model the interaction between patients and providers of primary care when antiinfective treatment is needed as a sequential choice in four stages. At the beginning of stage 1, nature assigns a health problem (mild respiratory or gastrointestinal infection) $i \in \{b, v\}$ to each individual, where $b$ is a bacterial infection and $v$ represents a viral infection. Consumers initially observe a symptom but cannot infer the type of infection they suffer from. We assume that both types of infections are equally likely. Hence, the probability of having a bacterial infection is $p = p[i = b] = p[i = v] = 1/2$.\footnote{The assumption of dichotomous health problems is quite common in the literature. For instance, Jelovac (2001) assumes that patients have the same probability of suffering from a “mild” illness as well as from a “severe” one.}

Patients recover naturally from viral infections after some time, by the end of stage 2. However, treatment with healing drugs ($NA$) suitable, for instance, to reduce body temperature (antipyretic or anti-inflammatory), cough (syrup) or nose constipation (spray), decreases the cost of illness because of quicker recovery and/or less discomfort. Treatment with antibiotics ($A$) is necessary to recover from a bacterial infection. On the other hand, antibiotics do not provide any additional benefit against viral infections. The depicted scenario applies for instance to mild respiratory tract infections in the community, such as colds, rhinofaringites, mild pneumonia and otitis.

In the market, there are two types of firms: $M$ general practitioners ($GP_j$, with $j \in [1, ..., M]$) and $M$ retailing pharmacies ($PH_j$), with $M \geq 2$. General practitioners can either be allowed to sell drugs directly to their patients or not, depending on patient’s cost of access to health care providers. Practices and pharmacies are located at equal distance around the circle and any couple of firms of different types is characterised by the same location. All the same types of firms have equal size.

Patients differ with respect to their spatial location between any two couples of providers and to the type of infection they suffer from. We normalise the total market distance to 1. Hence, a patient is located at distance $d_l \in [0, 1/M]$ from the nearest couple of providers at his left and at distance $d_r = 1/M - d_l$ from the providers at his right. The differentiation parameter $d$ can either be interpreted as a geographical distance between the individual and the provider location or the distance between
the individual’s preferences and the characteristics of the provider that maximises his utility.

In stage 1 individuals maximise their expected utility by choosing among the following 3 alternatives: 1. to consult a doctor and buy the prescribed drugs from a pharmacist afterwards; 2. to purchase some drugs directly from the pharmacist; 3. to do nothing and wait for natural recovery (Figure 1). The first alternative may either imply that the patient recovers at the end of stage 2 or that the patient needs an additional consultation to get an antibiotic treatment that was not initially prescribed. This is because the doctor’s diagnosis is not always correct. As for the second alternative, antibiotic treatment is not contemplated since this requires a doctor’s prescription. Patients will then receive an antipyretic/anti-inflammatory. This may imply that a consultation with a doctor is required later on (stage 4). Finally, sick individuals can decide to wait and do nothing, at least for some time (until the end of stage 3). If the patient suffers from a bacterial infection and does not recover naturally, a doctor’s consultation will then be necessary in stage 4.

2.1 Information structure

Patients are imperfectly informed about the level of services \( e_j \) provided by doctor \( j \). They know the minimum and the maximum levels of services that could be provided, hence observe the range of values \( e_j \in [e_{\text{min}}, e_{\text{max}}] \) and assume that each value in the range is equally likely. Patients then expect the average level of services \( \hat{e}_j = \bar{e} \equiv (e_{\text{min}} + e_{\text{max}}) / 2 \).

The level of services provided by GPs is related to diagnosis/prescription accuracy through a technological relationship which is the same for all GPs. We define \( p^c_j \in [0, 1] \) as the probability of a correct prescription by GP \( j \). More services increase the probability of a correct prescription through the following simple relationship \( p^c_j = g(e_j) = \beta e_j \) with \( \beta \in [0, 1] \). Consequently, given a level of services \( e_j \), the probability that the diagnosis is a bacterial infection and an antibiotic is prescribed is \( p^a_j = \frac{1}{2} e_j \). The probability of mistaken diagnosis will then be \( \frac{1}{2}(1 - \beta e_j) \).

Note that patients are assumed to expect the same levels of diagnostic services from dispensing and non-dispensing doctors. This hypothesis could be plausibly relaxed if the two types of practices provide different levels of services in equilibrium. Note, however, that the following Proposition 1 predicts that lower levels of diagnostic services increase doctor’s initial demand, ceteris paribus. This would in turn increase marginal benefits and, hence, lead to higher levels of diagnostic services. Consequently, an improvement in patients’ perceptions of the levels of diagnostic services provided may reduce the potential gap between dispensing and non-dispensing practices.
that higher intensity of services increases the probability of a correct prescription but
don’t know the true level of $e_j$. They expect to come back for a second consultation
if they do not recover by the end of stage 3. At this stage the nature of the infection
(bacterial) is fully revealed. Hence, patients correctly assume that the initial diagnosis
was wrong. Similarly, patients are assumed to realize that they need an antibiotic
if the waiting strategy has failed or drugs purchased from the pharmacist were not
effective at the end of stage 3.

We normalize $e_j$ to $1/\beta$ and set $e^{\text{min}} = 0$ and $e^{\text{max}} = 1/\beta$.

2.2 Expected net benefits of care

A consultation with a doctor has a cost $f (1 + e_j)$ and does not depend on the kind
of prescription which follows. In Switzerland, general practitioners are paid under a
pure fee-for-service scheme. This implies that total reimbursement for a consultation
depends upon the level of services provided.\footnote{For instance, a consultation has a fixed fee for the first five minutes allocated to the patient. A
diagnostic test to assess the type of infection implies an additional fee. We assume that there is a
continuum of services. Hence, the total fee increases with the intensity of care provided $e_j$.}
The cost of treatment with drugs, either antibiotic or antipyretic/anti-inflammatory, is $z$ ($z < f$).\footnote{We hypothesise that the cost of antibiotic doses and other types of drugs is the same. If the cost
of antibiotics is higher than the cost of other drugs, the patient more likely prefers to do nothing
or to see a pharmacist rather than to consult a general practitioner. This, however, does not have
relevant implications for our analysis, as shown later in Section 2.4.} Since primary health care
services are covered by compulsory health insurance contracts, patients pay only a
small fraction ($\alpha$) of the total cost of care.

Patients incur distance costs $td_j$ to purchase services from provider $j$, where $t$ is
the unit cost of distance. The discomfort, or the cost of time for recovering, when
patients are not given an effective treatment is $x$. We summarise the costs implied by
alternative treatments conditional upon the type of infection and the initial choice
of provider in Table 1. To simplify notation we define $w_{1j} = [f (1 + e_j) + z]$ and
$w_{2j} = [f (1 + e_j) + 2z]$.

For instance, consider a patient with a viral infection who decides to see doctor
$j$. The $GP$ may decide to prescribe an antipyretic/anti-inflammatory, without an
antibiotic. Consequently, the total cost of treatment conditional to the type of in-
festation (viral) and to the provider ($GP$) includes the partial cost of a consultation
($\alpha f (1 + e_j)$), plus the partial cost of prescribed drugs ($\alpha z$) that will be purchased
either from a pharmacy or, if allowed, directly from the practice, and the cost of
distance \((td_j)\). This gives \(\alpha w_{1j} + td_j\) in Table 1. However, if the \(GP\) makes a wrong
diagnosis, an antibiotic is prescribed as well. The total cost of drugs will increase to
\(2\alpha z\) and the total cost of treatment will be \(\alpha w_{2j} + td_j\).

### 2.2.1 Patient’s choice

A fully recovered patient has utility \(u^h > 0\) defined in monetary terms. Hence, the
expected net benefits from choosing practice \(j\) are defined as

\[
\hat{u}^{GP}_j = u^h - \frac{1}{2} \beta \hat{e}_j (\alpha \hat{w}_{1j} + td_j) - \frac{1}{2} \beta \hat{e}_j (\alpha \hat{w}_{2j} + td_j)
\]

\[
- \frac{1}{2} (1 - \beta \hat{e}_j) (\alpha \hat{w}_{2j} + td_j) - \frac{1}{2} (1 - \beta \hat{e}_j) (2\alpha \hat{w}_{1j} + 2td_j + x)
\]

\[
= u^h - \frac{1}{2} [ (3 - \beta \hat{e}_j) (\alpha \hat{w}_{1j} + td_j) + \alpha z + (1 - \beta \hat{e}_j) x] ,
\]

(1)

where \(\hat{w}_j\) is the expected value of \(w_j\).

The terms inside the brackets on the first line of equation (1) indicate the costs
of treatment when a viral infection is correctly diagnosed (first term), a bacterial
infection is correctly diagnosed (second term), a viral infection is wrongly diagnosed
and an antibiotic is prescribed (third term), and a bacterial infection is wrongly
diagnosed so that patients need a second consultation (fourth term).

The expected net benefits of waiting are derived in detail in the Appendix. We

\[
\hat{u}^W_j = u^h - x - \frac{1}{2} (\alpha \hat{w}_{2j} + td_j) .
\]

(2)

Similarly, we can write the expected net benefit of consulting a pharmacist as

\[
\hat{u}^{PH}_j = u^h - \frac{1}{2} [ \alpha (z + \hat{w}_{2j}) + x + 3td_j] .
\]

(3)

The above assumption on patients’ information implies that patient’s choice of
practice is initially based upon costly distance.\(^8\) Patients at distance \(d_j \leq 1/(2M)\)
from \(GP_l\) will then prefer to consult \(GP_l\) instead of \(GP_r\). Similarly, patients with

\(^8\)Brekke, Nuscheler and Straume (2006, 2007) assume that a proportion of patients is uninformed
and chooses a doctor according to distance. Gravelle and Masiero (2000) assume that patients
observe practice quality with an error and then learn by experience. These models focus on capitated
systems rather than fee-for service. Our assumption is useful to simplify the model and to focus on
patient’s alternative strategies rather than competition among providers of the same type. We then
ignore the impact of patient’s information structure on the choice of practice.
distance \(d_j > 1/(2M)\) will choose \(GP_r\). The choice of pharmacy follows the same rule since pharmacists are assumed to comply with doctor’s prescriptions.\(^9\) Consequently, the second stage of the game (choice between competing firms of the same type) identifies the couple of (preferred) providers \((GP^m, \, PH^m)\) that minimises the cost of access to antiinfective treatment for each patient.

From comparison between 1 and 3 for any \(j \in [1, .. , M]\), with \(\hat{e}_j = \bar{e}\) and \(\bar{w}_1 = f(1 + \bar{e}) + z\), we get

**Proposition 1** *Consultation with a GP is preferred to the initial advice of a pharmacist by all the patients if* \(x > \alpha (3\bar{w}_1 - 2z) \equiv x^{GP}\).

Patients are more likely to choose a GP if the expected level of diagnostic services (\(\bar{e}\) in \(\bar{w}_1\)) is lower. Since the main focus of our analysis is on antibiotic use under different incentives for doctors (with and without self-dispensing), we simplify the model by assuming \(x > x^{GP}\). This means that patients’ discomfort from waiting is great enough to imply that patients split in two groups: those who initially decide to consult a doctor and those who prefer to wait.

### 2.3 Demand for GP consultations

The proportion of patients who prefer a consultation with a GP is derived by comparison of (1) and (2). Patients will initially consult a GP if the minimum distance from a practice \((d^m = \min \{d_j\})\) is

\[
d^m < \frac{x - \alpha \bar{w}_1}{t} \equiv \delta_1.
\]

Hence, we have

**Proposition 2** *Patients prefer a visit with a GP rather than wait if disutility from waiting (x) minus the cost of treatment (\(\alpha \bar{w}_1\)) overcomes the cost of distance (td^m).*

By summing up the two market segments to the left-hand side and to the right-hand side of GP \(j\), we obtain doctor’s initial demand for consultations as\(^{10}\)

\[
D_j = 2N\delta_1 \equiv 2N \left(\frac{x - \alpha \bar{w}_1}{t}\right).
\]

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\(^9\)We neglect potential incentives to substitute brand names with generic drugs.

\(^{10}\)For comparison, doctor \(j\)’s initial demand with \(x < x^{GP}\) is \(2N(\delta_1 - \delta_2) = \frac{4N}{t} [x - \alpha (2\bar{w}_1 - z)] < D_j\), with \(\delta_2 = \frac{\alpha (3\bar{w}_1 - 2z) - x}{t}\) (see Appendix).
Proposition 3. Physician’s demand increases with the number of infected patients \((N)\), the discomfort from waiting \((x)\), and decreases with the cost of distance from the practice \((t)\), and the cost of consultation and treatment \((f(1 + \bar{e}) + z)\) in \(\bar{w}_1\).

Note that patient’s cost of access (the unit cost of distance \(t\)) reduces the demand for GP consultations. High levels of \(t\) may induce the regulator intervention to allow for direct dispensing.

The demand defined in (5) does not depend upon the number of practice firms \(M\) as far as some patients prefer to wait rather than to consult a GP.\(^{11}\) Doctor’s initial demand is the same for all GPs since it does not depend on physician’s actions. Hence, we drop the indexed notation and use \(D\) instead of \(D_j\) for GP’s initial demand in the following section.

2.3.1 Disappointment from delayed antibiotic treatment

Patients with a bacterial infection may receive a wrong diagnosis and then undertake an additional consultation to switch to antibiotic treatment. Those who decide to come back to the practitioner initially chosen, will increase doctor’s demand. Conversely, doctors may lose a proportion of patients who are not satisfied with antibiotic treatment delay. Some patients who need to see a doctor again after few days from the first consultation, may think that the doctor initially consulted was wrong. All these patients are now aware that they need an antibiotic and expect that any doctor will prescribe this treatment.

A patient will change the doctor if disappointment for inappropriate treatment, \(\theta\), plus the cost of distance overcome the cost of distance from joining the alternative practice, hence if \(td + \theta > t(\frac{1}{M} - d)\). Solving for \(d\) we find a critical distance\(^{12}\)

\[
d = \left(\frac{\frac{t}{M} - \theta}{2t}\right) = \delta^c,
\]

such that patients with \(d > \delta^c < \delta_1\) will switch out from practice \(j\). Consequently, the number of patients leaving the practice is \(S_{j}^{out} = \max \left\{ \frac{1}{2}(1 - \beta e_j)(\delta_1 - \delta^c)D, 0 \right\} \).

\(^{11}\)The initial demand for consultations for GP \(j\) when all the patients prefer a visit with a GP rather than wait is derived in the Appendix and decreases with the number of firms in the market.

\(^{12}\)Note that disutility from inappropriate treatment \((\theta)\) and disutility from waiting or late recovery \((x)\) is not the same. This is because we assume that \(\theta\) includes disappointment for the wrong diagnosis.
Similarly, we define the number of patients switching to practice \( j \) from the two neighbouring practices \( j^+ \) and \( j^- \) as 
\[
S_j^{\text{in}} = \max \left\{ \frac{1}{4} \left[ (1 - \beta e_j) + (1 - \beta e_{j^-}) \right] (\delta_1 - \delta^c) D, 0 \right\}.
\]

Using distances defined by (4) and (6) we can establish that

**Proposition 4** For \( \theta > \frac{t}{M} - 2(x - \alpha \bar{\omega}_1) \equiv \theta^* \) some patients always switch practice after a wrong diagnosis.

For instance, if disutility from inappropriate treatment (\( \theta \)) and disutility from waiting or late recovery (\( x \)) is the same, i.e. for \( \theta = x \), some patients switch in both directions provided that \( x > t/(3M) + 2\alpha \bar{\omega}_1/3 \equiv x^s \) since this satisfies \( \delta_1 - \delta^c > 0 \). Note that when all the patients prefer to consult a GP rather than waiting (see Appendix), there are at least some patients who change GP after a wrong diagnosis. This is because \( \theta > \theta^* \leq 0 \).

### 2.4 Physician’s behaviour

General practitioners have an objective function which depends upon the level of services provided and the cost for inappropriate treatment. For practice \( j \) we can write the following expression

\[
\pi_j = \left[ f (1 + e_j) - c \right] D + \frac{1}{2} \left( N/M - D \right) + \frac{1}{2} (1 - \beta e_j) D - S_j^{\text{out}} + S_j^{\text{in}} - \gamma e_j^2, \tag{7}
\]

where \( c \) is the fixed marginal cost of a consultation (\( c < f \)) and \( \gamma \) is the marginal cost of diagnostic services.\(^{13}\) The initial demand of the GP \( j \) is increased by the demand from patients with bacterial infection who initially decide to wait and do not recover without doctor’s prescription. The number of these patients is \( \frac{1}{2} \left( N/M - D \right) \). Patients with a bacterial infection who need a second consultation because of wrong diagnosis are \( \frac{1}{2} (1 - \beta e_j) D \).

The level of diagnostic services is assumed to be a local public good, i.e. it does not depend upon the number of patients diagnosed. The hypothesis suggests that improvements in diagnosis accuracy are related to the availability of a diagnostic technology rather than time spent with a patient.

\(^{13}\)Discounting for future profits is not applied since GPs maximize one-period profit. Although there is a time span between different stages of the game and patients realize the success or the failure of the initial consultation, this is indeed a short period of time (few days). Overlapping generations of patients are not considered in the model, nor is the possibility of repeated cases of infection in our cohort of patients. Our model is rather suitable to capture doctor’s behaviour under seasonal epidemic threat with annual recurrence.
2.4.1 Dispensing physicians

Dispensing physicians may differ from other practitioners for at least two reasons. Doctors may incur some costs for keeping drugs on stock. In this sense they are more similar to a pharmacy, compared to non-dispensing practices. A shortage in the stock may create some troubles if patients cannot receive the treatment when it is required. On the other hand, keeping drugs in stock for a certain period of time increases the risk of getting closer to the expiry date. Unsold drugs may imply some costs for the practice.

In Switzerland, dispensing physicians also get a mark-up on drugs prescribed. Other types of incentives are less likely. Plausibly, dispensing doctors are subject to pressure from pharmaceutical companies to increase prescriptions to the same extent as other doctors. Moreover, the doctors do not receive any additional fee for delivering drugs to their patients.

The objective function of the general practitioner defined by (7) can then be modified to include additional expected costs and benefits of self-dispensing as

\[
\pi_j^d = \left[ f (1 + e_j) - c + (\eta_1 - \eta_2) z \right] D^c - \gamma e_j^2, \tag{8}
\]

where

\[
D^c = D + \frac{1}{2} \left( \frac{N}{M} - D \right) + \frac{1}{2} (1 - \beta e_j) D - S_j^{out} + S_j^{in}
\]

is the total demand for consultations as it appears in (7), \( \eta_1 z \) is the mark-up on drugs directly dispensed and \( \eta_2 z \) represents the expected cost per patient of avoiding a prescription and keep stock of drugs.

2.5 Market equilibrium

Practice firms maximise their profits in a Nash-Cournot game where the levels of diagnostic services of the neighbouring competitors are given. Consequently, we simultaneously consider the set of \( M \) objective functions \( \pi_j \). Using (7) we derive profit with respect to the level of diagnostic services

\[
\frac{\partial \pi_j}{\partial e_j} = -2\gamma e_j - \left[ f (1 + e_j) - c \right] \frac{1}{2} \beta D \left[ 1 - (\delta_1 - \delta^c) \right]
\]

\[
+ f \left[ D + \frac{1}{2} \left( \frac{N}{M} - D \right) + \frac{1}{2} (1 - \beta e_j) D - S_j^{out} + S_j^{in} \right]. \tag{9}
\]

Since practice \( j \)'s profit depends upon the level of diagnostic services of the two neighbouring practices, \( j^+ \) and \( j^- \), we solve the set of first-order conditions \( \partial \pi_j / \partial e_j = \partial \pi_j / \partial e_{j^+} = \partial \pi_j / \partial e_{j^-} = 0 \). Substituting for \( \delta_1 \) and \( \delta^c \) we then get
Proposition 5  **A Cournot-Nash equilibrium in the level of diagnostic services is defined by**

\[
e^* = \frac{f (\lambda - \phi) + c \phi}{f \sigma + \frac{\sigma}{N}},
\]

(10)

where \( \lambda = \frac{1}{2M} + 2\delta_1 \), \( \phi = \delta_1 (1 - \delta_1 + \delta^c) \) and \( \sigma = \beta \delta_1 (2 - \delta_1 + \delta^c) \), with \( \lambda > \sigma > \phi \).

Note that patients’ disappointment for delayed antibiotic treatment, \( \theta \) in \( \delta^c \), increases the level of diagnostic services since it raises the cost of punishment (switching out of practice).\(^{14}\) The level of diagnostic services also increases with the number of infected patients \( (N) \) and decreases with the marginal cost of effort \( \gamma \) and the efficiency of services \( \beta. \)\(^{15}\)

When access is more costly patients are more likely to wait than to choose a practice. Access to GP consultations captured by the cost of distance \( t \) has a negative impact on the equilibrium level of services.\(^{16}\) The rationale is that the marginal gains from increasing the level of services provided to the patient is lower. However, lower levels of diagnostic services may imply higher rates of antibiotic use, as we will show later.

Similarly, the disutility of waiting, \( x \), increases GP attractiveness compared to the “doing nothing” strategy. Since the demand for consultations increases, the marginal gain from consultations increases as well. Hence, doctors have the incentive to improve the level of diagnostic services.\(^{17}\) On the other hand, the cost of a consultation and the cost of treatment \( (\alpha w_1) \) reduce the level of services. This is because patients are less likely to choose a GP initially and marginal gains from attracting additional patients are lower.

Finally, the number of providers, \( M \), has a double effect. First, it decreases diagnostic services since the marginal benefit from higher treatment accuracy is reduced \( (M \) reduces \( \lambda \) and \( \delta^c \) in \( \phi \)). This suggests that the density of general practices

\(^{14}\)A decrease in \( \theta \) reduces the denominator to a larger extent than the numerator in (10).

\(^{15}\)The marginal efficiency of services \( \beta \) in \( \phi \) and \( \sigma \) has a negative effect on \( e^* \) since \( f > c \) and \( \partial \phi / \partial \delta > 0 \).

\(^{16}\)The cost of distance has a negative impact on \( \delta_1 \) and a positive impact on \( \delta^c \). This leads to decreasing \( \lambda \). The impact on \( \phi \) is also negative provided that \( \theta < t + \frac{t}{2M^2} - 2(x - \alpha w_1) > \theta^r \). Similarly for \( \sigma \), since \( \partial \sigma / \partial t < \partial \phi / \partial t \). Consequently, \( t \) has a negative effect on all the parameters \( \lambda, \phi \) and \( \sigma \). Note that this effect is stronger for the numerator than the denominator in (10) since \( \partial \lambda / \partial t < \partial \sigma / \partial t < \partial \phi / \partial t \), at least for values of \( f \) very close to \( c \). As a result, \( e^* \) decreases with \( t \).

\(^{17}\)Disutility of waiting has a positive impact on \( \delta_1 \) and increases both \( \lambda, \sigma \) and \( \phi \). The final impact on \( e^* \) is positive.
may have relevant implications on the use of antibiotics. The result will be further discussed in the following section. Second, diagnosis accuracy increases since the density of practices tightens the competition for patients ($M$ reduces $\delta^c$ in $\sigma$). Hence, disappointed patients who may decide to switch practice contribute to decrease profitability of poor diagnostic services. The former effect is generally stronger than the latter.

2.5.1 Equilibrium with self-dispensing

Using the objective function for self-dispensing doctors defined by (8) and following the procedure for profit maximization above, we obtain

Proposition 6 A Cournot-Nash equilibrium in the level of diagnostic services with self-dispensing ($\eta_1 > 0$ and/or $\eta_2 > 0$) is defined by

$$e^{sd} = \frac{f(\lambda - \phi) + [c - (\eta_1 - \eta_2) z] \phi}{f \sigma + \frac{2\eta}{N}}.$$  \hspace{1cm} (11)

Note that $(\eta_1 - \eta_2) z$ increases or reduces the equilibrium level of services depending on the relative magnitude of $\eta_1$ and $\eta_2$. If the cost of antibiotic treatment delay and stocking drugs is higher than the mark-up from drug dispensing, i.e. $\eta_1 < \eta_2$, then $e^{sd} < e^*$. Diagnosis accuracy is lower for dispensing practices.\textsuperscript{18} This effect may reinforce the impact of the cost of access. An equilibrium with self-dispensing is generally marked by higher costs of distance compared to an equilibrium without direct dispensing. This is because the regulator allows for self-dispensing when the costs of access are high enough. This will have important implications on the per capita levels of antibiotic use.

\textsuperscript{18}As an alternative we could specify an objective function where dispensing doctors are aware that access to practices is more difficult in poorly urbanized areas. In this case doctors may internalize part of the costs of distance for the patient. If we substitute $\eta d$ for $\eta z$ we obtain a similar specification. Dispensing practitioners reduce their diagnostic services and are more likely to prescribe antibiotics to avoid a follow-up visit, i.e. additional costs of distance. A similar result could be obtained by assuming that poorly urbanized areas imply higher unit cost of distance ($t$) for the patient. This reduces patient’s access to the practice and the risk of loosing disappointed patients, who might consider to switch to alternative practices. The implication for the equilibrium level of services is always a decrease. Consequently, total antibiotic use under self-dispensing increases compared to dispensing restrictions.
2.6 Antibiotic prescriptions

Using the equilibrium level of diagnostic services in (10) and (11), we can summarize the number of antibiotic prescriptions per capita. A number of patients $\frac{1}{2}(\beta e^*) D$ receive a correct diagnosis of bacterial infection and are treated with antibiotics at the first consultation. Misdiagnosed patients with a viral infection also receive an antibiotic at the first consultation. These are $\frac{1}{2}(1 - \beta e^*) D$ patients. Some patients suffering from a bacterial infection with a wrong diagnosis at the first visit will be prescribed an antibiotic at the second visit. The number of these patients is $\frac{1}{2}(1 - \beta e^*) D$. Finally, some patients did not see any doctor initially (provided that $x < x^c$). Some of them, $\frac{1}{2}(\frac{N}{M} - D)$, have a bacterial infection and require a consultation with a doctor followed by an antibiotic prescription. Summing up all the patients receiving antibiotics and dividing by practice market share ($N/M$) we derive the per capita antibiotic use without and with self-dispensing as

$$a^* = \frac{1}{2} + (1 - \beta e^*) \delta_1 M, \quad (12)$$

$$a^{*d} = \frac{1}{2} + (1 - \beta e^{*d}) \delta_1 M. \quad (13)$$

The term inside the brackets in both equations indicate the number of antibiotic treatment prescribed for viral infections because of wrong diagnosis. Note that $a^* < a^{*d}$ since $e^* > e^{*d}$, ceteris paribus. However, if direct dispensing is allowed only if the unit cost of distance is above a given threshold, $\delta_1$ is reduced under self-dispensing, which in turn reduces antibiotic prescriptions per capita. The two opposite effects postulate that

**Proposition 7** Dispensing practices are more likely to overprescribe antibiotics compared to other practices, as far as the incentive to reduce diagnosis accuracy overcomes the negative impact on demand for consultations due to higher costs of access.

The empirical analysis in Section 3 will posit that the net effect of self-dispensing on antibiotic prescriptions per capita is likely to be positive.

Some interesting features can be straightforwardly derived from both (12) and (13). The number of practices ($M$) has two reinforcing effects on the per capita antibiotic use. First, it raises consumption since access to practices increases and patients are more likely to choose a doctor initially rather than wait. Second, it increases antibiotic consumption ($M$ in $e$, with $e \in \{e^*, e^{*d}\}$) because the level of
diagnosis accuracy is reduced. Doctors have lower marginal benefits from improving diagnostic services, which in turn increases inappropriate prescriptions.

Similarly, patient’s cost for waiting $x$ increases antibiotic use since patients are more likely to consult a GP ($x$ in $\delta_1$). However, since doctors expect higher benefit from consultations, diagnostic services are more valuable. The increase in diagnosis accuracy reduces the number of additional consultations. In other words, delayed antibiotic treatment is more profitable and tends to reduce total consumption ($x$ in $e$).

Surprisingly enough, the number of infected patients decreases the per capita antibiotic use. Although the total number of prescription is expected to increase, the per capita antibiotic use may slightly go down. We assumed that patients incur just one infection per period and that the external benefits from antibiotic use are not taken into account by doctor’s decisions. The incidence of infections increases doctor’s demand, hence the expected benefits from increases in diagnosis accuracy ($N$ raises $e$). This leads doctors to reduce inappropriate prescriptions per patient.

The marginal cost of diagnostic services ($\gamma$ in $e$) decreases the equilibrium levels and hence increases antibiotic use per capita. Conversely, the efficiency of the diagnosis ($\beta$ in $e$) improves the diagnosis accuracy and reduces per capita antibiotic consumption.

It is worth noticing that patient’s disappointment for antibiotic treatment delay ($\theta$ in $e$) reduces the use of antibiotics since it induces more diagnostic services and hence increases appropriate prescriptions.

3 Empirical analysis

3.1 Econometric specification

To assess the impact of dispensing practices on antibiotic consumption we use data on the per capita antibiotic use and possible determinants in 240 small market areas in Switzerland during the four quarters of 2002. The variables are summarized in Table 2.

Our theoretical model suggests that the per capita antibiotic use in the market area depends upon the number of physicians, the incidence of infections, the cost of access to alternative providers of primary care, and incentives attached to direct
dispensing of drugs.\textsuperscript{19} Plausibly, such characteristics as age, income and cultural aspects are related to the discomfort from waiting, $x$, the disappointment for antibiotic treatment delay, $\theta$, the cost of distance, $t$, and the marginal cost of a consultation, $c$, which affect doctor’s level of diagnostic services in (10) and (11).

The model hypothesises that a consultation with a GP is considered when patient’s health status is poor enough and doctors cannot affect the demand for medical treatment before an appointment has been taken. Consequently, the number of antibiotic prescriptions per individual can be measured by $a^*$ and $a^{sd}$ in (12) and (13). The probability of an antibiotic prescription during a consultation is affected by the incidence of bacterial infections and doctor’s practice style, i.e. doctors’ attitudes towards uncertainty on the nature of the infection.\textsuperscript{20}

A course of treatment with antibiotics is given by a number of standard daily doses. Using (12)-(13) we then define $DID_k = 1000a_k$, the number of defined daily doses per 1000 inhabitants in the market area $k$ ($k \in [1, \ldots, 240]$). We then postulate the following relationship:

$$DID_k = f(Y_k, POP_{lk}, INF_k, DPHY_k, DPHA_k, P_k, DBOR_k, DLAT_k, DHOS_k, NOSELF_k, SELF_k, DT_t),$$

(14)

where $Y_k$ is the average income in the area; $POP_{lk}$ is the percentage of the population in the $l$ age range; $INF_k$ is the incidence of bacterial infections (campylobacter and salmonella);\textsuperscript{21} $DPHY_k$ and $DPHA_k$ are respectively the density of physicians in the area and the density of pharmacies; and $P_k$ is the price of a defined daily dose of antibiotic.

$DBOR_k$, $DLAT_k$, and $DHOS_k$ are dummy variables. The first one captures

\textsuperscript{19}Many studies assume that the demand for physician’s services depends on a set of socioeconomic characteristics of the population (Hunt-McCool et al., 1994; Carlsen and Grytten 1998; Grytten and Sorensen, 2003).

\textsuperscript{20}Comparison of antibiotic prescription rates for children between Italy and Denmark shows that Italian children receive more courses of antibiotics than Danish children (Resi et al. 2003; Thrane et al., 2003). Kozyrskyj et al. (2004) show that the prescription of antibiotics for viral respiratory tract infections is less likely by pediatricians than by general practitioners. Also, physicians with a Canadian or an American training are less likely to prescribe a second line of antibiotics than those trained elsewhere. Finally, the age of physicians and the affiliation to a hospital has a significant impact on the prescribing practice. Trémolieres (2003) underlines experience, past and permanent training, information dissemination by the pharmaceutical industry and location as important factors affecting doctor’s prescriptions of antibiotics.

\textsuperscript{21}These are the leading causes of gastrointestinal infections. Since data are not available at local level, we use information at cantonal level.
any borderland effect with neighbouring countries. The second considers whether an area is mainly characterised by Latin culture (French- and Italian-speaking), or German culture. The third dummy accounts for at least one hospital in the area. $NOSELF_k$ and $SELF_k$ capture the impact of direct dispensing of antibiotic use. $NOSELF_k$ takes value equal to 1 if there are no dispensing practices in the area, 0 otherwise; $SELF_k$ takes value equal to 1 if the proportion of dispensing practices in the area is greater than 50%. The intermediate case where the proportion of dispensing practices is greater than 0 and lower than 50% represents our benchmark. $DT_t$ are time dummies ($t = 2, 3, 4$ since the first quarter is excluded to allow for price lags) identifying the 2002 quarters. $DT_4$ (October, November, December) is the baseline quarter.

The log-log specification offers an appropriate functional form for investigating the responsiveness of local per capita antibiotic sales to changes in the explanatory variables. Estimated coefficients can be interpreted as elasticities. We apply the log-log form to equation (14) assuming independently and identically normally distributed errors ($Model 1$).

To deal with the potential endogeneity problems related to prices and the incidence of infections, we consider the inclusion of lagged values. $P_k$ is the one-period lag for price of a defined daily dose. As for the incidence of infections, we use the average number of infections calculated over the years 1999-2001.

An econometric problem that could arise when estimating the demand model in (14) is the spatial correlation due to spatial dependency in antibiotics consumption. For this reason, we consider a second specification ($Model 2$). We estimate a spatial two-stage least-square model (S-2SLS) which assumes that the spatially weighted average of consumption in adjacent regions ($DID_{-k}$) affects the consumption in each region in addition to the standard explanatory variables. Spatial lags of exogenous variables and cantonal dummies are used as a set of instruments to estimate the mean antibiotic consumption in regions which are contiguous with region $k$.

Our data set contains a relatively small number of time periods ($t = 3$), a relatively large number of cross-sectional units ($N = 240$) and a zero within variation for most of

\begin{footnote}{Using a similar dataset, Filippini et al. (forthcoming) investigate determinants of small area variations in the use of outpatient antibiotics. They apply a linear specification for the purpose of measuring the welfare loss from unexplained variations and do not consider practice regulation.}

\begin{footnote}{For more detailed explanation see Anselin (2001) and Kelejian and Prucha (1998).}

17
the explanatory variables. When price endogeneity is taken into account observations for the first quarter \((t = 1)\) are not used. The only two variables that are changing over time (3 quarters) are the outpatient per capita consumption and the price of a daily dose. Consequently, the typical model for panel data, e.g. the least squares dummy variable model and the error components model are not appropriate.\(^{24}\) The estimation of Model 1 is then carried out with 720 observations and by using Ordinary Least Squares (OLS) with robust standard errors.\(^{25}\) In the standard OLS specification the error term is supposed to be independently and identically distributed. When the assumption is partially relaxed, the linearization/Huber/White/sandwich (robust) procedure allows to get estimates of the variance of the coefficients that are robust to the distribution assumptions. Instead, we use a two-stage least-square procedure when spatial dependency is taken into account (Model 2). Estimations are performed using the econometric software STATA.

### 3.2 Estimation results

Before focusing on the effect of self-dispensing, we briefly summarize the main results from the estimation of the two models (Table 3). The adjusted \(R^2\) indicates that the models explain approximately 75% of variations in the use of antibiotics.

The estimated spatial autoregressive parameter associated with the lag term \(DID_{-k}\) in Model 2 is significant and negative. This may suggest the evidence of positive consumption externalities across the areas.\(^{26}\)

Income elasticity varies between 0.16 and 0.22, which supports the hypothesis that antibiotics are normal goods.\(^{27}\) Our result is in accordance with other findings in the

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\(^{24}\)The reliability of these estimators depends on the extent of within-regional as well as between-regional variations of the dependent and the independent variables. As Cameron and Trivedi (2005) point out, the fixed-effects approach has an important weakness in that the coefficients of the explanatory variables are “very imprecise” if the variable’s variation over time is dominated by variation across regions (between variation).

\(^{25}\)We also run regressions with a between estimator and with and without spatial dependency. The results are generally confirmed.

\(^{26}\)A plausible explanation for this result is related to the double role of antibiotics. Antibiotics are used to cure bacterial infections and to prevent the spread of infections and bacterial resistance to other individuals. Consequently, the use of antibiotics in one area minimises the spread of infections in neighbouring areas. This implies that a smaller amount of antibiotics is required to obtain the same level of health benefits. Although patients’ imperfect information may suggest that this effect is not internalised by the individual, antibiotic prescribers such as general practitioners are quite likely to be aware of this effect.

\(^{27}\)Baye et al. (1997) find higher income elasticity (1.33) that may be related to differences in the
literature (Nilson and Laurell, 2005; Henricson et al., 1998; Thrane et al., 2003).

A higher proportion of children between 0 and 14 years of age increases antibiotic consumption in the area; conversely antibiotics are less likely to be prescribed in the areas with a larger proportion of individuals over 74 years of age compared to the baseline class. A negative impact is also observed for the proportion of individuals between 60 and over 74, although the coefficient is not significant.28

In both model specifications the coefficient of the incidence of infections exhibits the expected positive sign but is poorly significant. However, the estimated coefficients of the second and the third quarters (DT2 and DT3) are both negative and highly significant. This is in accordance with seasonal fluctuations observed by Elseviers et al. (2007) across Europe.

Antibiotic price has a negative and significant impact on antibiotic use in the area. Price elasticities in Model 1 (-0.72) and Model 2 (-0.71) are close to the estimates of Baye et al. (1997), who found negative compensated (-0.785) and uncompensated (-0.916) own-price effects for anti-infectives. Ellison et al. (1997) calculate price elasticities unconditional on drug (cephalosporins) expenditure using US wholesales data from 1985 to 1991. Their estimates range between -0.38 and -4.34.

The physicians’ density is positively and significantly associated with the local per capita antibiotic use. Estimated elasticities are around 0.11 in both specifications. Similarly, an increase in the density of pharmacies leads to higher levels of per capita outpatient antibiotic use in the area. The estimated coefficient ranges between 0.61 and 0.63.

As for the impact of self-dispensing, we find that the proportion of practices without direct dispensing of drugs (NOSELF) has a negative effect on antibiotic use, although the coefficient is not significant. Consequently, we cannot reject the hypothesis that areas without dispensing practices and areas with a relatively small proportion of self-dispensing practices (below 50%) exhibit similar levels of antibiotic use per capita. However, when the proportion of dispensing practices is relatively high (more than 50%), the effect on consumption is positive and significant. The estimated coefficients suggest that a one percent increase in the proportion of dispensing practices beyond 50% will increase per capita antibiotic sales by 0.32% (0.29% when population under study and the type of antibiotics considered (only penicillins and tetracyclines).

28Similar results are obtained, for instance, by Mousquès et al. (2003), who investigate a panel of general practitioners prescribing antibiotics for rhynopharingeal infections.
spatial dependency is taken into account).

It is worth noticing that the correlation between the rate of dispensing practices and the density of pharmacies in the area is remarkable. This may suggest that self-dispensing improve access to medical services. Note, however, that our estimated coefficient for dispensing practices is adjusted for the density of pharmacies and the density of all practices. This implies that direct dispensing of drugs may increase antibiotic consumption beyond the levels usually attained by satisfactory access to medical services.

It can also be argued that the density of pharmacies is not a good indicator for access to antibiotic treatment in the area. Indeed, travelling costs for the patient may vary consistently. Consider, for instance, two small areas of the same size but different number of pharmacies and inhabitants. The two areas may have the same number of providers per inhabitant but the average patient’s distance from the pharmacy may be different. To address this point we run separate estimations with the density of the population as an additional regressor. This captures the level of urbanization of the areas and can be used as a proxy for travelling distances. The variable is never significant, nor it changes the results of the other covariates significantly.

4 Conclusions

In developed countries, prescribing and dispensing of antibiotics are generally kept separate. Switzerland, however, represents an exception. The rationale for direct dispensing is that prescribers improve access to pharmaceuticals in areas with low density of pharmacies. However, the regulation of self-dispensing may not be efficient in preventing antibiotic misuse. It has been suggested that prescribing costs per patient in dispensing practices are higher than costs in non dispensing practices (Morton-Jones and Pringle, 1993).

We investigated the impact of dispensing practices on the per capita outpatient antibiotic consumption by combining a theoretical and an empirical approach. Our model hypothesises that the regulator who allows for direct dispensing of drugs does not take economic incentives on dispensing practices into account. Dispensing practices may reduce diagnosis accuracy of bacterial infections compared to non-dispensing practices, thus leading to higher rates of antibiotic use per capita. The rationale behind this may be three-fold: the additional costs for stocking drugs and
the risk of drugs expiring, the exposure to advertising pressure by pharmaceutical firms, and the tendency to meet patients’ preferences for antibiotic treatment.

Using an ad-hoc econometric model we estimated the impact of self-dispensing on the demand for outpatient antibiotics in Switzerland. Our findings support the prediction of the theoretical frame that dispensing practices induce higher rates of antibiotic use, *ceteris paribus*. The adjustment of economic incentives attached to dispensing practices may then contribute to reduce the inappropriate use of antibiotics and contain the threat of bacterial resistance.
Appendix

Expected net benefits of waiting

If a patient decides to wait he/she will recover naturally at the end of stage 2 with probability 1/2 (viral infection). If, however, the patient is still sick by the end of stage 2, the nature of his/her infection is assumed to be perfectly revealed (bacterial infection). The patient knows that an antibiotic is required and needs a doctor for the prescription. Using Table 1 we calculate the expected net benefits of waiting as

\[
\hat{u}_j^W = u^h - \frac{1}{2}x - \frac{1}{2} (x + \alpha \hat{w}_{2j} + td_j) \\
= u^h - x - \frac{1}{2} (\alpha \hat{w}_{2j} + td_j). 
\]

(15)

Expected benefits of pharmacist’s advice

If the patient initially asks for a pharmacist’s advice an antipyretic/anti-inflammatory will always be purchased (antibiotics requires a doctor’s prescription). This either reduces the recovering time or other kind of discomfort. With probability 1/2 (bacterial infection) the patient will need a doctor’s prescription (antibiotic) in stage 3. The expected net benefits of consulting a pharmacist are

\[
\hat{u}_j^{PH} = u^h - \frac{1}{2} (\alpha z + td_j) - \frac{1}{2} (x + \alpha \hat{w}_{2j} + 2td_j) \\
= u^h - \frac{1}{2} [\alpha (z + \hat{w}_{2j}) + x + 3td_j]. 
\]

(16)

Patient’s choice

Comparison of (1) and (2) gives \( \hat{u}_j^{GP} > \hat{u}_j^W \) for any \( j \in [1,..,M] \) if

\[
x > \alpha \bar{w}_1 + td^m,
\]

(17)

where \( \bar{w}_1 = f (1 + \hat{e}) + z, d^m = \min \{d_j\} \) and \( \hat{e}_j = \frac{1}{2^{j+1}}. \)

The inequality in (17) is satisfied for those patients whose minimum distance from a practice is

\[
d^m < \frac{x - \alpha \bar{w}_1}{t} \equiv \delta_1.
\]

(18)

Similarly, comparison between (1) and (3) gives \( \hat{u}_j^{GP} > \hat{u}_j^{PH} \) if

\[
d^m > \frac{\alpha (3\bar{w}_1 - 2z) - x}{t} \equiv \delta_2,
\]

(19)
which is satisfied if patient’s copayment for consultations and treatment is lower than
the disutility for ineffective treatment ($x$).

A patient will then choose a consultation with the nearest GP provided that
inequalities (18) and (19) are satisfied. This requires $\delta_1 > d^m > \delta_2$, hence $x > \alpha (2\bar{w}_1 - z) \equiv x^W$. Note, however, that $\delta_2$ is negative for $x > \alpha (3\bar{w}_1 - 2z) \equiv x^{GP}$
and $x^{GP} > x^W$. Consequently, $x > x^{GP}$ ensures that all the patients initially prefer to consult a GP rather than a pharmacist and a proportion of patients $\delta_1$ initially prefer a consultation with a GP rather than waiting. For $x^{GP} \geq x > x^W$ the proportion of patients who initially choose a GP is reduced to $\delta_1 - \delta_2$ since $\delta_2 > 0$. Some patients prefer to wait (those with $d^m > \delta_1$) and some patients prefer to see a pharmacist (those with $d^m < \delta_2$). To summarize, we have $\hat{u}_j^W > \hat{u}_j^{PH}$ for any $d_j > \delta_1$ and $\hat{u}_j^W < \hat{u}_j^{PH}$ for any $d_j < \delta_2$.

**Consultation with GPs as a unique choice**

For $\delta_1 < 1/(2M)$ some patients whose distance from the nearest practice is higher
than $\delta_1$ prefer to wait rather than consulting a GP. On the other hand, for $\delta_1 \geq 1/(2M)$ all the patients prefer a consultation with a GP than waiting. Using (4) we derive

$$x^c = \frac{t}{2M} + \alpha \bar{w}_1, \quad (20)$$

the critical value of disutility from waiting above which all the patients prefer to consult a GP as an initial choice.

For $x \leq x^c$ only some patients prefer to consult a GP, a proportion $\delta_1$ provided that $x > x^{GP}$. Hence, doctor’s initial demand is defined by (5) in Section 2.3 if $x^{GP} < x^c$, i.e. if the number of practices is small enough: $M < \frac{t}{4w_j(1+\bar{w})}$.

Substituting (20) into (5) we then find $GP_j$’s initial demand when consultations are preferred by all the patients

$$D_j \left[ x \geq x^c \right] = \frac{N}{M}. \quad (21)$$
References


Information Services Division (ISD) of the National Health System (NHS) in Scotland, Information and Statistics Division, Practitioner Services Division (PSD), http://www.isdscotland.org [December, 2006].


Table 1: The total cost of treatment depends upon the strategy chosen by the patient (the type of health care provider initially chosen), the prescribed drugs (\(A=\)antibiotics, \(N.A=\)antipyretic/anti-inflammatory) and the type of infection \((b=\)bacterial, \(v=\)viral).

<table>
<thead>
<tr>
<th>Infection</th>
<th>Prescription</th>
<th>Cost of different patient’s strategies</th>
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</thead>
<tbody>
<tr>
<td>(v)</td>
<td>(N.A)</td>
<td>(x) (\alpha z + td_j) (\alpha w_1 + td_j)</td>
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<tr>
<td>(v)</td>
<td>(A+N.A)</td>
<td>(x) (\alpha w_2 + td_j)</td>
</tr>
<tr>
<td>(b)</td>
<td>(N.A+N.A)</td>
<td>(x + \alpha w_{2j} + td_j)</td>
</tr>
<tr>
<td>(b)</td>
<td>(N.A+N.A)</td>
<td>(x + \alpha w_{2j} + 2td_j) (x + 2(\alpha w_{1j} + td_j))</td>
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\(\alpha\), \(\beta\), \(\gamma\), \(\delta\), \(\epsilon\), \(\zeta\), \(\theta\), \(\iota\), \(\kappa\), \(\lambda\), \(\mu\), \(\nu\), \(\xi\), \(\omicron\), \(\pi\), \(\rho\), \(\sigma\), \(\tau\), \(\upsilon\), \(\phi\), \(\chi\), \(\psi\), \(\omega\)

<table>
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<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std dev</th>
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<td>Defined daily doses per 1000 inhabitants</td>
<td>11.714</td>
<td>13.061</td>
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<td>(Y)</td>
<td>Income per capita defined in CHF</td>
<td>23465</td>
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<td>(POP_1)</td>
<td>Proportion of 0-14 in total population</td>
<td>0.1658</td>
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<td>(POP_2)</td>
<td>Proportion of 15-25 in total population</td>
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<td>0.0173</td>
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<td>(POP_3)</td>
<td>Proportion of 26-59 in total population</td>
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<td>(POP_4)</td>
<td>Proportion of 60-74 in total population</td>
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<td>0.0213</td>
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<tr>
<td>(POP_5)</td>
<td>Proportion of over 74 in total population</td>
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<td>0.0190</td>
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<td>Incidence of common gastrointestinal infections (salmonella and campylobacter) in 100000 inhabitants</td>
<td>114.69</td>
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<td>(DPHY)</td>
<td>Density of physicians for 100000 inhabitants</td>
<td>565.21</td>
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<td>(DPHA)</td>
<td>Density of pharmacies for 100000 inhabitants</td>
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<td>(P)</td>
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<td>Whether or not the area borders other countries</td>
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<td>-</td>
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<td>(DLAT)</td>
<td>Whether an area has a Latin (French and Italian) or a German culture</td>
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<td>-</td>
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<td>(DHOS)</td>
<td>Whether or not there is at least one hospital in the area</td>
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<td>Whether or not there are no self-dispensing practices in the area</td>
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<tr>
<td>(SELF)</td>
<td>Whether or not there is a majority of self-dispensing practices in the area</td>
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Table 2: Variables notation and summary statistics.
<table>
<thead>
<tr>
<th>Covariates</th>
<th>Coefficients</th>
<th>St. Err.</th>
<th>p-value</th>
<th>Coefficients</th>
<th>St. Err.</th>
<th>p-value</th>
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Table 3: Parameter estimates
Figure 1: Patient’s alternatives to tackle a mild respiratory/gastro-intestinal infection: 1. to consult a doctor immediately; 2. to consult a pharmacist first (if practices cannot sell drugs directly); 3. to do nothing and wait.