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*Dispensing practices and antibiotic use*

by

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# Dispensing practices and antibiotic use

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## Abstract

Regulation of prescription and dispensing of antibiotics has a twin purpose: to enhance access to antibiotic treatment and to reduce inappropriate use of drugs. Nevertheless, incentives on antibiotics 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 antibiotic consumption by means of spatial econometric estimators. The investigation exploits data from small geographic areas in a country where both regimes - with and without dispensing physicians - are possible. We find evidence that dispensing practices increase antibiotic use after controlling for determinants of demand and access, and spatial effects. 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 the two primary aspects of access to primary health care. In most developed countries, the main role of family physicians is to prescribe drugs without direct dispensing. Doctors are not allowed to sell drugs directly to their patients in several OECD countries such as Italy, Germany and Scandinavian countries. Still, direct dispensing of drugs is possible within some countries. For instance, one Scottish region (Highland) includes almost 20% of the total number of dispensing doctors in Scotland (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 some exceptions across the country.

The reason for separating drug prescribing and dispensing is to optimise drug treatment by avoiding a conflict of interest for the prescriber and by ensuring good practice in dispensing (Trap and Hansen, 2003). Since dispensing physicians may have an incentive to induce drug consumption in order to increase their revenues, it is suggested that a regulatory policy that allows physicians to sell drugs directly to the patient may lead to sub-optimal levels of drug consumption (Chou et al., 2003; Holloway, 2005; Morton-Jones and Pringle, 1993; Nelson, 1987). Abood (1989) shows that dispensing doctors charge higher retail prices, whereas Rischatsch and Trottmann (2009) suggest that dispensing physicians have a greater probability of prescribing drugs that offer high margin, when compared with non-dispensing physicians.

Nevertheless, the benefits of separating drug prescribing and dispensing are still unclear. Direct dispensing of drugs may increase patients' benefits because of improved access to drug treatment in areas where geographical barriers represent a problem. Moreover, there are important external effects of consumption which affect, in particular, the optimal use of anti-infective drugs. Among these drugs, consumption externalities are certainly relevant for antibiotics. These externalities can be summarized by the effect of bacterial resistance, which reduces antibiotic effectiveness, and the effect of infection prevention, which extends benefits from antibiotic use to other individuals (Rudholm, 2002). The recent literature on antibiotic manufacturers suggests, for instance, that incentives for pharmaceutical firms to minimise resistance are not optimal since companies enjoy a too short period of monopoly benefits from their antibiotic effectiveness (Herrmann, 2010). As with respect to the retailing market, the benefits of good prescribing practices and low levels of resistance to antibiotics generated by the separation of drug prescribing and dispensing must be weighed

against the costs of limited access and low levels of infection prevention.

The purpose of this article is to explore the role of practice regulation in enhancing access to antibiotic treatment and in reducing inappropriate use of antibiotics. We propose a theoretical model to investigate the behaviour of different types of general practitioners in a competitive environment with imperfect information on the nature of patient infections. We then test empirically the behaviour of dispensing practices.

We apply the standard Salop (1979) horizontal product differentiation model to the market for community antibiotic treatment by incorporating imperfect information about the type of infection, diagnosis errors and alternative treatments under a fee-for-service remuneration scheme for physicians. The market for outpatient antibiotic treatment we have in mind applies, for instance, to Switzerland where doctors receive a consultation fee which varies depending on the time allocated to the patient and the diagnostic tests performed. In such a case, dispensing doctors may include additional costs for drugs available with them in stock and gain a margin on antibiotics sold to the patient. We show that the interaction between imperfect information on the nature of a patient's infection and economic incentives to dispensing practices may increase the likelihood of antibiotic prescriptions, *ceteris paribus*. The rationale is that self-dispensing physicians may increase their revenue by selling more antibiotics under uncertainty on the nature of a patient's infection. To some extent, this effect may overcome the opposite effect of restrictions on antibiotic use due to difficulties in access to health care treatment in areas where the density of providers is relatively poor.

In the health economics literature, we are not aware of any theoretical approach to the behaviour of dispensing practices that considers competition among physicians under uncertainty on the nature of patient's infection and spatial aspects of drug consumption. Two studies (Liu et al., 2009; Rischatsch and Trottmann, 2009) investigate physician prescribing decisions in the choice between generic and brand-name drugs. Though, these studies assume that physicians act as monopolists and spatial aspects are neglected.

To investigate the impact of dispensing practices on outpatient antibiotic consumption empirically, we use a demand model which takes into account the main determinants of antibiotic use. Moreover, we consider spatial aspects of consumption by means of an appropriate econometric estimator. We exploit data from small geographical areas in a country (Switzerland) where two regimes - prescribing physicians and dispensing physicians - are possible, which provides the ground for a natural experiment. Related to this exercise is the study by Windmeijer et al. (2006) who investigate the impact of promotional activities

by pharmaceutical companies on GP prescription behaviours. The authors suggest that prescriptions are positively affected by promotion expenditure but do not consider different types of practices and focus on the market of anti-hypertensives and anti-depressant. Also, Trap and Hansen (2002) examine differences in the rationality of the prescription in relation to diagnosis and symptoms between dispensing and non dispensing doctors for one antibiotic substance (cotrimoxazole). Since dispensing doctors are found to prescribe an antibiotic 2.5 times more frequently than non dispensing doctors, the authors conclude that dispensing practices may lead to increasing health hazards and bacterial resistance. The authors do not account for access and consumption externalities.

Although one can hardly identify the socially optimal level of antibiotics empirically, it is advisable to adjust for external effects when investigating the behaviour of different types of practices. Spatial aspects of consumption are generally disregarded in empirical studies on drug prescription and consumption. Nonetheless, antibiotic drugs are generally used to treat respiratory and gastrointestinal infections which are among the most common infectious diseases acquired in the community. As discussed by Hess et al. (2002), these infections are characterized by a spreading process across regions, i.e. the infection initiates in one region and then spreads across other regions. As an example of the spatial spread of an infection see, for instance, Werneck et al. (2002). Spatial-econometric estimators in health economics have been recently applied by Lachaud (2007), Moscone et al. (2007), Moscone and Tosetti (2009) and Filippini et al. (2009b). Moscone et al. (2007) and Moscone and Tosetti (2009) empirically investigate the determinants of regional health expenditures in the US and in England using panel data. Both studies suggest the importance of taking spatial aspects into account when modelling the utilization of health care services.

The remaining of 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 antibiotic treatment**

Our model of the market for antibiotic treatment provided by primary care physicians (GPs) is an application of the standard circular product differentiation model (Salop, 1979; Gravelle, 1999). We incorporate new features: imperfect information about the nature of the infection, doctor's diagnosis errors, and alternative types of treatment. We focus on

the interaction between patients and general practitioners when anti-infective treatment<sup>1</sup> is needed as a sequential choice in three stages. At the beginning of stage 1, nature assigns a health problem (mild respiratory or gastro-intestinal infection),  $i \in \{b, v\}$ , to each of the  $N$  individuals uniformly distributed along a circle line, where  $b$  is a *bacterial* infection and  $v$  represents a *viral* infection.<sup>2</sup> Consumers initially observe a symptom but cannot infer the type of infection they suffer from. To simplify the presentation, we assume that both types of infections are equally likely. Hence, the probability of having a bacterial infection is  $p = p[i = b] = p[i = v] \equiv 1/2$ .<sup>3</sup>

Individuals maximise their expected utility from choosing a practice. In the market there are  $M$  general practice firms ( $GP_j$ , with  $j \in [1, \dots, M]$ ), with  $M \geq 2$ . General practitioners can either be allowed to sell drugs directly to their patients or not, depending on the legislative frame set by the health authority. Practices are located at equal distance around the circle. All practices have equal size. Finally, whatever the type of practices, we assume that  $M$  pharmacies are also in the market and located nearby each practice<sup>4</sup>

The patient's choice of practice depends on the perceived level of diagnosis accuracy. Patients differ with respect to their location and the type of infection. We normalise the total market distance to 1. Hence, a patient is located at distance  $d_l \in [0, 1/M]$  from the nearest practice at his left and at distance  $d_r = 1/M - d_l$  from the practice at his right. The differentiation parameter  $d$  can either be interpreted as a geographical distance between the individual and the provider location, it could be the distance between the individual's preferences and the characteristics of the provider that maximises his utility.

In stage 2 the doctor makes a prescription based on a diagnosis signal. The patient recovers naturally from viral infections by the end of stage 2 (see Figure 1). Our depicted scenario applies, for instance, to mild respiratory tract infections in the community, such as colds, rhynofaringites, mild pneumonia and otitis. We assume that a treatment undertaken using healing drugs, suitable for instance to reduce body temperature (antipyretic or

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<sup>1</sup>Anti-infective is a general term that encompasses antibacterials, antibiotics, antifungals, antiprotozoans and antivirals. In this paper we focus on the choice between antibacterials and antivirals and the terms antibacterials and antibiotics will be used interchangeably.

<sup>2</sup>Dichotomous health problems are considered, for instance, in Jelovac (2001) where patients have the same probability of suffering from a "mild" illness as well as from a "severe" one.

<sup>3</sup>The main results are not affected when this assumption is relaxed. See the appendix for the more general case where  $p[i = b] \neq p[i = v]$  with  $0 < p[i = b] < 1$  and  $0 < p[i = v] < 1$ . We shortly discuss the implications of this case in section 2.6.

<sup>4</sup>This implies that patients do not incur additional costs of transportation to buy drugs after a consultation with a GP. Clearly, we also hypothesize that pharmacies are not allowed to change a doctor's prescription.

anti-inflammatory), cough (syrup) or nose constipation (spray), decreases the cost of illness because it offers quicker recovery and/or less discomfort. This is always prescribed independent of any antibiotic treatment. Contrarily, treatment with antibiotics ( $A$ ) is necessary to recover from a bacterial infection. Antibiotics do not provide any additional benefit against viral infections. Since a doctor's diagnosis is not always correct, a second consultation may be required later on (stage 3) if the patient suffers from a bacterial infection and an antibiotic treatment was not initially prescribed.

[Figure 1]

## 2.1 Information structure

The accuracy of a GP's prescription is related to the level of diagnostic services provided. We define  $p_j^c \in [0, 1]$  as the probability of a correct diagnosis by GP  $j$ . More diagnostic services increase the probability of a correct diagnosis through the following simple relationship  $p_j^c(e_j) = \beta e_j$ , where  $e_j$  represents the level of diagnostic services provided by the practice and  $\beta \in [0, 1]$  is a parameter. Consequently, the probability that the diagnosis is a bacterial infection and an antibiotic is correctly prescribed is  $pp_j^c = \frac{1}{2}\beta e_j$ . The probability of mistaken diagnosis will then be  $\frac{1}{2}(1 - \beta e_j)$ . We assume that doctors rely on diagnostic tests to decide upon the type of treatment to be prescribed. Alternatively, we could assume that doctors share the results of diagnostic tests with patients and cannot cheat on this information.

Before a consultation patients are imperfectly informed about the level of diagnostic services ( $e_j$ ) provided by the practice. They roughly assume that each value in the range  $e_j \in [e^{\min}, e^{\max}]$  is equally likely. Consequently, patients expect an average level of services  $\hat{e}_j = \frac{1}{2}e^{\min} + \frac{1}{2}e^{\max} \equiv \bar{e}$ . We normalise  $e_j$  to  $1/\beta$  and set  $e^{\min} = 0$  and  $e^{\max} = 1/\beta$ .

Patients are aware that higher intensity of diagnostic services increases the probability of a correct prescription but don't know the true level of  $e_j$ . They expect a second consultation if they do not recover by the end of stage 2.

## 2.2 Expected net benefits of care

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. General practitioners are paid under a pure fee-for-service scheme. This implies that total reimbursement for a



consultation depends upon the level of diagnostic services provided.<sup>5</sup> 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. In Switzerland this depends upon the type of insurance plan chosen since different deductible schemes are available.

We assume that a consultation with a doctor has a cost  $f(1 + e_j)$ , where  $f$  is the fixed fee. This cost depends on the level of diagnostic services provided ( $e_j$ ) but does not depend on the kind of prescription which follows. Treatment with antipyretic/anti-inflammatory drugs does not vary with the type of infection; the cost of this treatment is set to zero. On the other hand, a course of treatment with antibiotics has a fixed cost of  $z$  ( $z < f$ ).

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  $\theta$ . We summarise the costs implied by alternative treatments conditional upon the type of infection in Table 1. To simplify notation we define  $w_j = f(1 + e_j)$ . A treatment without antibiotics is denoted as *NA*.

For instance, consider a patient with a viral infection consulting doctor  $j$ . If the *GP* decides to prescribe an antipyretic/anti-inflammatory without an antibiotic, the total cost of treatment includes the partial cost of a consultation ( $\alpha w_j$ ), plus the cost of distance ( $td_j$ ). This gives  $\alpha w_j + td_j$  in Table 1. However, if the *GP* makes a wrong diagnosis, the cost of treatment will increase by  $\alpha z$  since an antibiotic will be later prescribed. The total cost will then be  $\alpha(w_j + z) + td_j$ .

[Table 1]

### 2.3 Demand for GP consultations

A fully recovered patient has utility  $u^h > 0$  defined in monetary terms. Using Table 1 we can write the expected net benefits from choosing practice  $j$  as

$$\begin{aligned} \hat{u}_j &= u^h - \frac{1}{2}\beta\hat{e}_j(\alpha\hat{w}_j + td_j) - \frac{1}{2}\beta\hat{e}_j(\alpha\hat{w}_j + \alpha z + td_j) \\ &\quad - \frac{1}{2}(1 - \beta\hat{e}_j)(\alpha\hat{w}_j + \alpha z + td_j) - \frac{1}{2}(1 - \beta\hat{e}_j)(2\alpha\hat{w}_j + \alpha z + 2td_j + \theta) \\ &= u^h - \frac{1}{2}[(3 - \beta\bar{e})(\alpha\bar{w} + td_j) + (2 - \beta\bar{e})\alpha z + (1 - \beta\bar{e})\theta]. \end{aligned} \tag{1}$$

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<sup>5</sup>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. Hence, the total fee increases with the intensity of care provided.

The terms inside the brackets 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 assumption on patients' information implies that a patient's choice of practice is based upon costly distance.<sup>6</sup> 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 distance  $d_j > 1/(2M)$  will choose  $GP_r$ . By summing up the two market segments to the left-hand side and to the right-hand side of  $GP_j$ , we derive a doctor's initial demand for consultations as:

$$D_j = \frac{N}{M}. \quad (2)$$

The demand for consultations for  $GP_j$  decreases with the number of firms in the market. Since a doctor's initial demand is the same for all  $GPs$ , we drop the indexed notation and use  $D$  instead of  $D_j$  in the following section.

### 2.3.1 Antibiotic treatment delay

Patients with a bacterial infection who receive a wrong diagnosis need an additional consultation to switch to antibiotic treatment. We assume that patients disappointed with the practice because of health complications or loss of revenue due to antibiotic treatment delay, will not leave the current practice. They will, at least, wait before the infection has been cured. This hypothesis simplifies the model and is perhaps quite realistic since the nature of the infection is now fully revealed and an antibiotic will be prescribed by the current practice.

The total demand for consultations can then be derived as:

$$D^c = D + \frac{1}{2}(1 - \beta e_j)D. \quad (3)$$

Patients with a bacterial infection who need a second consultation because of wrong diagnosis are  $\frac{1}{2}(1 - \beta e_j)D$ .

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<sup>6</sup>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 a patient's alternative strategies rather than the effects of competition among providers. We then ignore the impact of a patient's information structure on the choice of practice.

## 2.4 Physician's objective

The general practitioner has an objective function ( $\pi_j$ ) which depends upon the benefits and costs of diagnostic services provided. Using (3) we can write

$$\pi_j = [f(1 + e_j) - c]D^c - \gamma e_j^2, \quad (4)$$

where  $c$  is the fixed marginal cost of a consultation ( $c < f$ ) and  $\gamma$  is the marginal cost of diagnostic services.<sup>7</sup>

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.

### 2.4.1 Dispensing physicians

Dispensing physicians may differ from other practitioners for at least two reasons. Doctors may incur some costs when keeping drugs on stock. In this sense they are more similar to a pharmacy than to non-dispensing practices. A shortage of stock implies risks in case patients are unable to receive the required treatment when it is needed. On the other hand, large stocks of drugs that have been hoarded increase the risk of getting closer to the expiry date. Unsold drugs may imply some costs for the practice.

In Switzerland, dispensing physicians get a mark-up on drugs prescribed. Obviously, dispensing doctors are subject to pressure from pharmaceutical companies to increase prescriptions to the same extent as other doctors.<sup>8</sup>

We modify the objective function of the general practitioner defined by (4) to include the expected costs and benefits of self-dispensing as

$$\pi_j^d = [f(1 + e_j) - c]D^c + \left(D^c - \frac{D}{2}\right)(z - \eta) - \gamma e_j^2, \quad (5)$$

where  $z$  is the unit price of drugs dispensed to the patient and  $\eta \leq z$  represents the unit cost of drugs on stock. The number of antibiotic treatments sold is obtained by summing up the number of patients with a bacterial infection (correctly diagnosed) plus the number

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<sup>7</sup>Although there is a time span between different stages of the game and patients realise the success or the failure of the initial consultation, this is a short period of time (few days) and discounting for future profits is not applied. For similar reasons, overlapping generations of patients are not considered, nor is the possibility of multiple infections in the cohort of patients. Our model is maybe suitable to capture doctor's behaviour under seasonal epidemic threat with annual recurrence.

<sup>8</sup>Windmeijer et al. (2006) find that GP prescription behaviour is affected by pharmaceutical promotion but the magnitude of this effect is not assessed separately for dispensing and prescribing doctors.

of viral infections with a wrong diagnosis, and the number of patients who require a second consultation because a bacterial infection was not initially diagnosed. The total amount of treatments can be summarised by  $D^c - D/2$ .

## 2.5 Market equilibrium

Practice firms maximise their profits in a Nash-Cournot game where the levels of diagnostic services provided by neighbouring competitors are given. Consequently, we simultaneously consider the set of  $M$  objective functions  $\pi_j$ . Using (4) we derive profit with respect to the level of diagnostic services

$$\frac{\partial \pi_j}{\partial e_j} = -2\gamma e_j - [f(1 + e_j) - c] \frac{1}{2} \beta D + f \left[ D + \frac{1}{2}(1 - \beta e_j) D \right]. \quad (6)$$

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  $D$  in (6) and solving for the level of diagnostic services we then get

**Proposition 1** *A Cournot-Nash equilibrium in the level of diagnostic services is defined by*

$$e^* = \frac{3f - (f - c)\beta}{2(2\frac{M}{N}\gamma + f\beta)}. \quad (7)$$

The level of diagnostic services increases with the number of infected patients ( $N$ ) and decreases with the marginal cost of effort  $\gamma$  and the efficiency of services  $\beta$ . The number of providers,  $M$ , leads to decrease in diagnostic services since the marginal benefit from higher treatment accuracy is reduced. This suggests that the density of general practices may have relevant implications on the use of antibiotics. The result will be further discussed in the following section.

### 2.5.1 Equilibrium with self-dispensing

Using the objective function for dispensing doctors defined by (5) and following the procedure for profit maximisation above, we obtain

**Proposition 2** *A Cournot-Nash equilibrium in the level of diagnostic services with self-dispensing is defined by*

$$e^{*d} = \frac{3f - [f - c + (z - \eta)]\beta}{2(2\frac{M}{N}\gamma + f\beta)}. \quad (8)$$

Note that  $(z - \eta)$  increases or decreases the equilibrium level of services depending on the relative magnitude of  $z$  and  $\eta$ . Clearly, if antibiotic price is high enough, then  $e^{*d} < e^*$ , *ceteris paribus*. Diagnosis accuracy is lower for dispensing practices. However, this result may be partially offset by the relatively low density of practices in areas where direct dispensing is allowed. If the cost of access to health care providers in one area is higher because of the reduced number of practices, i.e.  $M$  is low, the equilibrium level of services in (8) is also higher. Consequently, the negative impact of a markup on sales ( $z - \eta > 0$ ) on the level of diagnostic services provided may be compensated by the positive effect of higher costs of access in markets with dispensing practices. This aspect will have important implications on the per capita levels of antibiotic use since it represents the crucial point for the comparison of prescribing practices in different areas.

## 2.6 Antibiotic prescriptions

Using the equilibrium level of diagnostic services in (7) and (8), we can summarise antibiotic prescriptions per capita. A number of patients  $\frac{1}{2}(\beta e^*)D$  receive 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 consultation will be prescribed an antibiotic at the second visit. The number of these patients is  $\frac{1}{2}(1 - \beta e^*)D$ . Summing up all the patients who received antibiotics and dividing by practice market share ( $N/M$ ) we derive the per capita antibiotic use without and with self-dispensing as

$$a^* = \left(1 - \frac{\beta}{2}e^*\right), \quad (9)$$

$$a^{*d} = \left(1 - \frac{\beta}{2}e^{*d}\right). \quad (10)$$

Some interesting features can be straightforwardly derived from both (9) and (10) through the level of diagnostic services available. The marginal cost of diagnostic services ( $\gamma$  in  $e$ ) increases antibiotic use per capita, whereas the efficiency of the diagnosis ( $\beta$  in  $e$ ) improves the diagnosis accuracy and reduces per capita antibiotic consumption. This is because diagnostic services reduce the number of false prescriptions. For  $e^* = e^{\max} = 1/\beta$ , GPs would prescribe  $a^* = 1/2$ . All patients with a bacterial infection would receive an antibiotic at the first consultation. Conversely, none of the patients with a viral infection would receive an antibiotic. Because of uncertainty  $\beta < 1$ , which implies  $e^* < e^{\max}$ . Consequently, at least in some cases antibiotics will not be correctly prescribed.

The number of practices ( $M$  in  $e$ ) increases antibiotic consumption because the level of accuracy of diagnosis is reduced. Doctors have lower marginal benefits from improving diagnostic services, which in turn increases inappropriate prescriptions.

The number of infected patients,  $N$ , decreases the per capita antibiotic use. Although the total number of prescriptions increases, per capita antibiotic use may decrease. We assumed that patients incur just one infection per period and that the external benefits from antibiotic use are not taken into account under the doctor's decisions. The incidence of infections increases a doctor's demand and therefore, the expected benefits from increases in diagnosis accuracy ( $N$  raises  $e$ ). This leads doctors to reduce inappropriate prescriptions per patient.

From comparison between (9) and (10) note that  $a^* < a^{*d}$  for  $e^* > e^{*d}$ , *ceteris paribus*. We then postulate the following proposition

**Proposition 3** *Dispensing practices are likely to prescribe more antibiotics per capita compared to other practices as long as positive mark-ups from selling antibiotics directly to the patient remain.*

The result of Proposition 3 holds provided that the density of practices is the same in markets where dispensing is permitted or not. As mentioned above, the rationale behind direct dispensing of drugs is to reduce the costs of access to health care treatment. The regulator's primary objective is to allow for direct dispensing of drugs in areas where the density of practices is relatively low when compared to other areas. This implies that the positive effect of the mark-up on antibiotic sales may not completely offset the impact of the higher cost of access (low density of practices) as compared to markets where direct dispensing is not allowed. The magnitude of these opposite effects is a critical aspect that we will try to disentangle by means of an empirical approach in the following session. The hypothesis we want to test can be summarised by the following proposition

**Proposition 4** *In areas where dispensing practices are allowed, individual consumption of antibiotics is higher when compared with other areas if the positive impact of mark-up on antibiotic sales is not completely offset by the higher costs of access to health care services.*

Whether or not dispensing practices lead to higher levels of antibiotic use compared to non dispensing practices clearly depends upon the strength of the incentive related to the mark-up on antibiotic sales.

### 3 Empirical analysis

#### 3.1 Econometric specification

The theoretical framework presented in section 2 (equations 7, 8, 9 and 10) suggests that in a region defined by a circle the demand for antibiotics is influenced by the following factors: physician density, population density, price of antibiotics, price of a consultation, probability of a correct diagnosis and incentives attached to direct dispensing of drugs. Moreover, it is important to underline that the demand equations (9) and (10) have been derived for a region characterised by individuals with homogeneous socioeconomic variables such as income, age, and cultural factors.

For the empirical part of this paper we use aggregate data for the year 2002 on the consumption of antibiotics for 240 Swiss regions<sup>9</sup> and we will adopt a representative consumer approach, namely for each region we define the dependent variable as the per capita antibiotic consumption. Further, the econometric specification of the demand for antibiotics hypothesises that some socioeconomic variables vary across the regions.<sup>10</sup>

Moreover, in order to estimate one demand function rather than the two represented by (9) and (10), the empirical model includes a dummy variable representing the difference of practice styles and incentives attached to the possibility of direct dispensing of drugs.

We build on the theoretical framework and on a previous empirical study on the determinants of small area variations in the use of outpatient antibiotics (Filippini et al., 2009a) to specify the following empirical model based on a log-log functional form:

$$\begin{aligned} \ln DID_k = & \beta_0 + \beta_1 \ln Y_k + \beta_2 \ln POP_{1k} + \beta_3 \ln POP_{2k} + \beta_4 \ln POP_{4k} & (11) \\ & + \beta_5 \ln POP_{5k} + \beta_6 \ln INF_k + \beta_7 \ln DPHY_k + \beta_8 \ln DPHA_k \\ & + \beta_9 \ln DENPOP_k + \beta_{10} \ln PA_k + \beta_{11} \ln PC_k + \beta_{12} DBOR_k \\ & + \beta_{13} DLAT_k + \beta_{14} DHOS_k + \beta_{15} NOSELF_k + \beta_{16} SELF_k. \end{aligned}$$

$DID_k$  is the per capita outpatient antibiotic use in the  $k^{th}$  market area measured in defined daily doses per 1000 inhabitants.  $DPHY_k$ ,  $DPHA_k$ ,  $DENPOP_k$  are respectively the density of physicians, pharmacies and population in the area; and  $PA_k$  is the price of a

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<sup>9</sup>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. Direct dispensing is not allowed in Geneva, Vaud, Balle ville, Ticino and Argau. In some regions of the other cantons direct dispensing is permitted.

<sup>10</sup>The literature on determinants of the demand for physician's services emphasises the role of socioeconomic characteristics of the population and practice styles (Hunter-McCool et al., 1994; Carlsen and Grytten 1998; Grytten and Sorensen, 2003). More closely to antibiotics, the literature suggests that cultural aspects may influence the use of antibiotics. For instance, Italian children receive more courses of antibiotics than Danish children (Resi et al. 2003; Thrane et al., 2003).

defined daily dose of antibiotic and  $PC_k$  represents the price of a standard consultation with a general practitioner defined at cantonal level and captured by the point values (weights) calculated for the reimbursement of services provided by general practitioners in 2001.<sup>11</sup>  $POP_{lk}$  is the percentage of population in the  $l$  age range and  $INF_k$  is the incidence of bacterial infections (campylobacter and salmonella).<sup>12</sup> These two variables are proxies for the probability of a correct diagnosis. Further, the model (11) considers some explanatory variables not explicitly defined in the theoretical models (9) and (10).  $Y_k$  is the average income in the area;  $DBOR_k$ ,  $DLAT_k$ , and  $DHOS_k$  are dummy variables. The first one captures any borderland effect with neighbouring countries. The second considers whether an area is characterised by Latin culture (French- and Italian-speaking), or German culture. The third dummy accounts for at least one hospital in the area.

Finally, since we cannot directly measure the magnitude of the mark-up on antibiotic sales we use the status of practices, i.e. whether a practice can sell drugs directly to their patients or not, as an indicator for a positive mark-up on antibiotic prescriptions. Therefore, two dummy variables,  $NOSELF_k$  and  $SELF_k$ , are introduced in the model to capture the impact of direct dispensing on 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.

From the empirical point of view, the inclusion of practice styles and incentives attached to direct dispensing of drugs ( $NOSELF_k$  and  $SELF_k$ ) represents the novelty of the current approach compared to our previous study (Filippini et al., 2009a) since practice regulation has not been considered before. Moreover, we use a log-log functional form whereas a linear specification has been previously applied for the purpose of measuring the welfare loss from heterogeneous attitudes towards antibiotic use.<sup>13</sup>

For the estimation of equation (11) we have quarterly data for the dependent variable

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<sup>11</sup>In Switzerland, a detailed fee-for-service system with more than 4600 items is applied for the reimbursement of health care providers. A given number of points is assigned to each type of service according to time, complexity and facilities. The cantons apply different values to the basic point, which reflects the heterogeneity in the costs of services across the country. Therefore, the point value can be interpreted as a proxy for the price of a consultation.

<sup>12</sup>These are the leading causes of gastrointestinal infections. Since data are not available at local level, we use information at cantonal level.

<sup>13</sup>Clearly, the model does not allow to disentangle the possible mismatch between antibiotic prescriptions, antibiotic sales and antibiotic use since detailed data on these figures are not available. We focus on determinants of antibiotic use and assume patient's non-compliance to be a negligible factor.



- per capita antibiotic use - and for one independent variable - the price of a daily dose -, whereas for the remaining explanatory variables only yearly data are available.<sup>14</sup> Therefore, we resolve to estimate equation (11) on a quarterly basis.<sup>15</sup> A summary statistics of variables used in the empirical analysis is provided in Table 2.

[Table 2]

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.

The correct econometric approach to the estimation of equation (11) has to deal with two main issues: the possible endogeneity of price and infection variables and the possible spatial correlation of antibiotic consumption across regions. To deal with potential endogeneity problems, we consider the inclusion of lagged values.  $PA_k$  is the one-period lag for price of a defined daily dose. As for the incidence of infections, we use the average incidence of bacterial infections calculated over the years 1999-2001.

As for the spatial aspect, it is worth noting that regional antibiotic consumption may be affected by individuals' and physicians' attitudes towards antibiotic consumption as well as the presence of infection disease in adjacent regions. These spatial externality problems can be taken into account by means of adequate spatial econometrics estimators.<sup>16</sup> To incorporate spatial effects into our regression model we can follow two approaches: the spatial-lag model and the spatial-error model. In this paper we adopt the spatial-error model.<sup>17</sup> As suggested by Moscone and Knapp (2005), this approach is more relevant when the distribution of residuals in different regions displays spatial correlation. Residual may be spatially correlated if aggregated shocks hit regional health authorities or there are

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<sup>14</sup>It is worth noting that the quarterly variation of the explanatory variables is generally very low.

<sup>15</sup>We also estimated equation (11) on a yearly basis, that is to say by considering the yearly average value of antibiotic consumption as the dependent variable and by pooling quarterly data. In the latter case, the standard errors are biased because the explanatory variables have exactly the same value in all quarters. For this reason, we report the results of quarterly estimations. Anyway, the estimation results using the pooling as well as the average approaches are similar to those reported here.

<sup>16</sup>For a general introduction and discussion of spatial econometrics, see Anselin (1988, 2001). For an application of spatial econometric methods in health economics see Moscone and Knapp (2005), Moscone, Knapp and Tosetti (2007), Costa-Font and Moscone (2008), Filippini et. al. (2009a, 2009b).

<sup>17</sup>In order to test the presence of spatial autocorrelation we considered two tests: the Moran's I and Geary's C statistics. The null hypothesis is rejected by both tests, which suggests evidence of spatial autocorrelation in antimicrobial use among Swiss regions.

unobservable risk factors concentrated across the areas. In our case, this effect may be due, for instance, to an infection disease breakdown spreading across the country.<sup>18</sup>

The spatial-error model can be defined as:

$$DID = X\beta + \varepsilon, \tag{12}$$

$$\varepsilon = \mu + W\lambda\varepsilon, \tag{13}$$

where  $DID$  is a  $k \times 1$  vector of observations on antibiotic consumption per capita;  $X$  is the  $k \times q$  matrix of explanatory variables;  $\beta$  is the vector of regression parameters,  $\varepsilon$  is a vector of errors,  $W$  is a matrix of spatial weights,  $\lambda$  is the spatial-autoregressive coefficient and  $\mu$  is a vector of errors that are assumed to be independently and identically distributed. Note from equation (13) that errors depend on the weighted average of errors in neighbouring regions. The matrix of spatial weights contains information on the spatial association between observational units. We construct a contiguity matrix indicating which regions share a borderland. According to this proximity criterion, the elements of the spatial weight matrix are 1 if location  $i$  is adjacent to location  $j$ , and zero otherwise.

When price endogeneity is taken into account observations for the first quarter ( $t = 1$ ) are not used. Accordingly, we provide estimations for three quarters. For comparison purposes, equation (11) is also estimated using Ordinary Least Squares (OLS) with robust standard errors. 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 us to get estimates of the variance of the coefficients that are robust to the distribution assumptions. 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 equation (11) using the spatial-errors approach (Table 3).

Income elasticity varies between 0.03 and 0.23, which supports the hypothesis that antibiotics are normal goods.<sup>19</sup> Our result is in accordance with other findings in the literature (Nilson and Laurell, 2005; Henricson et al.,1998; Thrane et al., 2003).

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<sup>18</sup>We also estimate equation (11) by means of a spatial-lag autocorrelation approach. The results are similar to those presented in this paper.

<sup>19</sup>Baye et al. (1997) find higher income elasticity (1.33) that may be related to differences in the population under study and the type of antibiotics considered (only penicillins and tetracyclines).

Concerning the impact of the age structure of the population on antibiotic consumption we can observe that only young and elderly people seem to have an impact. A higher proportion of children between 0 and 14 years of age increases antibiotic consumption in an area. Conversely, antibiotics are less likely to be prescribed in areas that have a larger proportion of individuals who are over 74 years of age compared to the baseline class.<sup>20</sup>

[Table 3]

In all model specifications the coefficient of the incidence of infections exhibits the expected positive sign but is poorly significant. Also, the population density seems not to have an impact on antibiotic consumption

The values of price elasticity of antibiotics obtained for the second and the fourth quarters 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 irrespective of drug (cephalosporins) expenditure using US wholesales data from 1985 to 1991. Their estimates range between  $-0.38$  and  $-4.34$ . The coefficient on price of doctor consultations is not significant. Although expensive consultations imply higher diagnosis effort, which may reduce inappropriate prescriptions of antibiotics, this hypothesis is not confirmed by our results.

The physicians' density is positively and significantly associated with local per capita antibiotic use. Estimated elasticities varies between 0.08 and 0.12. 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 0.62 and 0.79.

As for the impact of direct 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 0.48%.

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<sup>20</sup>Similar results are obtained, for instance, by Mousquès et al. (2003), who investigate a panel of general practitioners prescribing antibiotics for rhynopharyngeal infections.

It is worth noticing that the correlation between the rate of dispensing practices and the density of pharmacies in an area is remarkable. This may suggest that self-dispensing improves 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 with 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 does it change the results of the other covariates significantly.

The result of the LM-error test reported at the bottom of Table 3 suggests, at least for the second and third quarters, the presence of spatial dependency . Finally, as can be observed from Table 4, the OLS results are similar to the results obtained with the spatial-error model (Table 3) and confirm the findings on dispensing practices.

[Table 4]

## 4 Conclusions

Prescribing and dispensing of drugs are important aspects of access to primary health care. In most developed countries, these aspects are kept separate and doctors are not allowed to sell drugs directly to their patients. The separation of prescribing drugs and dispensing drugs has recently proved to be effective in reducing drug expenditure, for instance in Taiwan (Chou et al., 2003). However, the separation of drug prescribing and dispensing may be costly in terms of limited access to drug treatment and low levels of infection prevention. In Switzerland, physicians are allowed to sell drugs directly to their patients in most cantons, with some exceptions across the country.

In this paper, we model dispensing practices of Swiss physicians using a theoretical and an empirical approach. For this purpose, we extend the classical (circular) product

differentiation model (Salop, 1979; Gravelle, 1999) with horizontal and vertical dimensions. We allow for different types of general practitioners (with and without direct dispensing) and imperfect information on the nature of patient's infection (viral or bacterial). GPs can reduce errors in prescribing by increasing the level of diagnostic services provided to their patients. We show that the interaction between imperfect information on the nature of patient's infection and incentives to dispensing practices may reduce diagnosis accuracy and, consequently, increase the likelihood of antibiotic prescriptions. This effect may overcome benefits from enhancing access to health care treatment in areas with relatively poor density of providers.

The rationale behind lower diagnostic effort by dispensing practitioners as compared to prescribing practitioners may be three-fold: additional costs for stocking drugs and the risk of drugs expiring, exposure to advertising pressure by pharmaceutical firms, and tendency to meet patients' preferences for antibiotic treatment.

Using data on antibiotic consumption from small geographical areas in Switzerland, we investigate the effects of dispensing practices empirically. Our findings indicate that dispensing practices induce higher rates of antibiotic use, after controlling for patient characteristics, epidemiological factors and access to drug treatment. Moreover, spatial aspects of infectious diseases and antibiotic consumption are taken into account by appropriate spatial-econometrics estimators (Moscone et al., 2007; Moscone and Tosetti, 2009). There will be scope for additional incentives to dispensing practices to reduce the inappropriate use of antibiotics and contain the threat of bacterial resistance.

## Appendix

We extend the basic model in the main text by relaxing the assumption  $p^b = p^v$ . Let the probability of bacterial infection be  $p^b$ , and the probability of viral infection be  $p^v$ , with  $p^b + p^v = 1$ . Consequently, the probability of different treatment strategies can be written as:

- $p^b p_j^c$  : correct diagnosis of bacterial infection (antibiotic prescription);
- $p^v p_j^c$  : correct diagnosis of viral infection (treatment without antibiotics);
- $p^b (1 - p_j^c)$  : wrong diagnosis of bacterial infection (antibiotic needed but not initially prescribed);
- $p^v (1 - p_j^c)$  : wrong diagnosis of viral infection (unnecessary antibiotic prescription).

Replacing  $p_j^c = \beta e_j$  in probabilities above and using the costs of treatment in table (1), we can write equation (1), i.e. the expected net benefits from choosing practice  $j$ , as:

$$\begin{aligned}\hat{u}_j &= u^h - p^v \beta \hat{e}_j (\alpha \hat{w}_j + td_j) - p^b \beta \hat{e}_j (\alpha \hat{w}_j + \alpha z + td_j) \\ &\quad - p^v (1 - \beta \hat{e}_j) (\alpha \hat{w}_j + \alpha z + td_j) - p (1 - \beta \hat{e}_j) (2\alpha \hat{w}_j + \alpha z + 2td_j + \theta).\end{aligned}\quad (14)$$

Substituting  $\bar{e}$  for  $\hat{e}_j$  and  $1 - p^b$  for  $p^v$ , we can simplify (14) as

$$\hat{u}_j = u^h - \left[1 + p^b (1 - \beta \bar{e})\right] (\alpha \bar{w} + td_j) - \left[1 - \beta \bar{e} (1 - p^b)\right] \alpha z - p^b (1 - \beta \bar{e}). \quad (15)$$

Total demand for consultations is obtained by substituting  $p^b$  for  $1/2$  in equation (3):

$$D^c = D + p^b (1 - \beta e_j) D. \quad (16)$$

The number of patients with a bacterial infection who need a second consultation because of wrong diagnosis are  $p^b (1 - \beta e_j) D$ . Consequently, the GP's objective function without direct dispensing is:

$$\pi_j = [f (1 + e_j) - c] D^c - \gamma e_j^2. \quad (17)$$

The number of antibiotic prescriptions is derived by summing up the number of prescriptions for bacterial infections at the first and the second consultation,  $p^b D$ , and the number of unnecessary prescriptions because of wrong diagnosis or viral infection,  $(1 - p^b)(1 - \beta e_j) D$ :

$$D^A = D \left[1 - \beta e_j (1 - p^b)\right]. \quad (18)$$

Using (18), we can write the GP's objective function with direct dispensing as:

$$\begin{aligned}\pi_j^d &= [f (1 + e_j) - c] D^c + D^A (z - \eta) - \gamma e_j^2 \\ &= [f (1 + e_j) - c] D^c + D \left[1 - \beta e_j (1 - p^b)\right] (z - \eta) - \gamma e_j^2.\end{aligned}\quad (19)$$

The first-order conditions for profit maximization for prescribing and dispensing are:

$$\frac{\partial \pi_j}{\partial e_j} = -2\gamma e_j - [f (1 + e_j) - c] p^b \beta D + f \left[D + p^b (1 - \beta e_j) D\right], \quad (20)$$

$$\frac{\partial \pi_j^d}{\partial e_j} = \frac{\partial \pi_j}{\partial e_j} - \beta (1 - p^b) D (z - \eta). \quad (21)$$

Solving (21) and (20) for the Nash-Cournot equilibrium levels of diagnostic services, we then get

$$e^* = \frac{f (1 + p^b) - (f - c) \beta p^b}{2 \left(\gamma \frac{M}{N} + f \beta p^b\right)}, \quad (22)$$

$$e^{*d} = e^* - \frac{(1 - p^b) (z - \eta) \beta}{2 \left(\gamma \frac{M}{N} + f \beta p^b\right)}. \quad (23)$$

Using (18), we can write the equilibrium level of antibiotic prescriptions per capita,  $D^{*A}/D$ , as:

$$a^* = \left[ 1 - \beta e^* (1 - p^b) \right], \quad (24)$$

$$a^{*d} = \left[ 1 - \beta e^{*d} (1 - p^b) \right]. \quad (25)$$

Note that when the probability of bacterial infection is not constrained to 1/2, new insights can be derived from comparison with eqs. (9)-(10) in the main text. In particular, an increase in the incidence of bacterial infections ( $p^b$ ) has unclear impact on antibiotic consumption per capita. From (16) we see that the incidence of bacterial infections increases the demand for consultations since more patients with mistaken diagnosis need a second consultation. This implies two opposite incentives. The marginal benefit of diagnostic services is higher. However, an increase in diagnostic services reduces the demand for repeated consultations.

Finally, the effect of dispensing practices is lower when the probability of bacterial infection is close to 1. Conversely, when the probability of bacterial infection is relatively low, additional marginal gains generated by diagnostic services are smaller and antibiotics will be prescribed more frequently.

## References

- Aboud RR, "Physician dispensing: issues of law, legislation and social policy", *American Journal of Law & Medicine*, 14, 4, 307-52, 1989.
- Anselin L, "Spatial Econometrics", in: Baltagi B, *A Companion to Theoretical Econometrics*, Oxford: Basil Blackwell, 310-330, 2001.
- Baye MR, Maness R, and Wiggins SN, "Demand systems and the true subindex of the cost of living for pharmaceuticals", *Applied Economics*, 29, 1179-1189, 1997.
- Brekke KR, Nuscheler R and Straume OR, "Gatekeeping in health care", *Journal of Health Economics*, 26, 149-170, 2007.
- Brekke KR, Nuscheler R and Straume OR, "Quality and location choices under price regulation", *Journal of Economics & Management Strategy*, 15, 207-227, 2006.
- Cameron AC and Trivedi PK, *Microeconometrics: methods and applications*, New York: Cambridge University Press, 2005.
- Carlsen F and Grytten J, "More physicians: improved availability or induced demand?", *Health Economics*, 7, 495-508, 1998.
- Chou Y, Yip WC, Lee C-H, Huang N, Sun Y-P and Chang H-J, "Impact of separating drug prescribing and dispensing on provider behaviour: Taiwan's experience", *Health Policy and Planning*, 18, 3, 316-329, 2003.
- Costa-Font J and Moscone F, "The impact of decentralization and inter-territorial interactions on Spanish health expenditure", *Empirical economics*, 34, 167-184, 2008.
- Ellison SF, Cockburn I, Griliches Z and Hausman J, "Characteristics of demand for pharmaceutical products: an examination of four cephalosporins", *RAND Journal of Economics*, 28, 426-446, 1997.
- Elseviers M, Ferech M, Vander Stichele RH and Goossens H, "Antibiotic use in ambulatory care in Europe (ESAC data 1997-2002): trends, regional differences and seasonal fluctuations", *Pharmacoepidemiology and Drug Safety*, 16, 1, 115-123, 2007.
- Filippini M, Masiero G and Moschetti K, "Small area variations and welfare loss in the use of outpatient antibiotics", *Health Economics, Policy and Law*, 4, 55-77, 2009a.
- Filippini M, Masiero G and Moschetti K, "Regional consumption of antibiotics: a demand system approach", *Economic Modelling*, 26, 1389-1397, 2009b.
- Gravelle H, "Capitation contracts: access and quality", *Journal of Health Economics* 18, 315-340, 1999.
- Gravelle H and Masiero G, "Quality incentives in a regulated market with imperfect infor-



mation and switching costs: capitation in general practice”, *Journal of Health Economics* 19, 6, 1067-1088, 2000.

Grytten J and Sorensen R, “Practice variation and physician-specific effects”, *Journal of Health Economics*, 22, 403-418, 2003.

Henricson K, Melander E, Molstad S, Ranstam J, Hanson BS, Rametsteiner G, Stenber GP and Melander A, “Intra-urban variation of antibiotic utilization in children: influence of socioeconomic factors”, *The Journal of Clinical Pharmacology*, 54, 8, 653-657, 1998.

Herrmann M, “Monopoly pricing of an antibiotic subject to bacterial resistance”, *Journal of Health Economics*, 29, 1, 137-150, 2010.

Hess GR, Randolph SE, Arneberg P, Chemini C, Furlanello C, Harwood J, Roberts M and Swinton J, “Spatial aspects of disease dynamics”, in *The Ecology of Wildlife Diseases*, Hudson PJ. et al., eds, Oxford University Press, 102–118, 2002.

Holloway K, “Impact of health care systems on drug use”, Institut Pasteur Euroconferences: Mastering anti-infective therapies, Paris, October 20-21, 2005, <http://www.pasteur.fr> [January, 2006].

Hunt-McCool J, Kiker BF and Chu Ng Y, “Estimates of the demand for medical care under different functional forms”, *Journal of Applied Econometrics*, 9, 2, 201-218, 1994.

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

Jelovac I, “Physicians’ payment contracts, treatment decisions and diagnosis accuracy”, *Health Economics*, 10, 1, 9-25, 2001

Kelejian H and Prucha IR, “A Generalized Spatial Two-stage Least Squares procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances”, *Journal of Real Estate Finance and Economics*, 17, 1, 99-121, 1998.

Kozyrskyj A, Dahl ME, Chateau DG, Mazowita GB, Klassen TP and Law BJ, “Evidence-based prescribing of antibiotics for children: role of socioeconomic status and physician characteristics”, *Canadian Medical Association or its licensors*, 171, 139-145, 2004.

Lachaud J-P, “HIV prevalence and poverty in Africa: Micro- and macro-econometric evidences applied to Burkina Faso”, *Journal of Health Economics*, 26, 483–504, 2007.

Liu Y-M, Yang Y-HK and Hsieh C-R, “Financial incentives and physicians’ prescription decisions on the choice between brand-name and generic drugs: Evidence from Taiwan”, *Journal of Health Economics*, 28, 341-349, 2009.

Morton-Jones TJ and Pringle MA, “Prescribing costs in dispensing practices”, *British Med-*

*ical Journal*, 306, 6887, 1244-1246, 1993.

Moscone F and Knapp M, "Exploring the spatial pattern of mental health expenditure", *Journal of Mental Health Policy and Economics*, 8, 205-217, 2005.

Moscone F, Knapp M and Tosetti E, "Mental health expenditure in England: A spatial panel approach", *Journal of Health Economics*, 26, 842-864, 2007.

Moscone F and Tosetti E, "Health expenditure and income in the United States", *Health Economics*, 2009.

Mousquès J, Renaud T, and Scemama O, "Variabilité des pratiques médicales en médecine générale: la prescription d'antibiotiques dans la rhinopharyngite aiguë", Centre de Recherche d'Etude et de Documentation en Economie de la Santé, *CREDES, série analyse*, 2003.

Nelson S, "Drug dispensing by MDs stirs controversy", *Hospitals*, 61, 10, 66-7, 1987.

Nilson P and Laurel MH, "Impact of socioeconomic factors and antibiotic prescribing on penicillin-non susceptible *Streptococcus pneumoniae* in the city of Malmö", *Scandinavian Journal of Infectious Diseases*, 37, 6, 436-441, 2005.

Resi D, Milandri M, Moro ML and the Emilia Romagna Study Group on the Use of Antibiotics in Children, "Antibiotic prescriptions in children", *Journal of Antimicrobial Chemotherapy*, 52, 282-286, 2003.

Rischatsch M, Trottmann M, "Physician dispensing and the choice between generic and brand-name drugs - Do margins affect choice?", *Working Paper No. 0911*, University of Zurich, 2009.

Rudholm N, "Economic implications of antibiotic resistance in a global economy", *Journal of Health Economics*, 21, 1071-1083, 2002.

Salop SC, "Monopolistic competition with outside goods", *Bell Journal of Economics*, 10, 141-156, 1979.

Thrane N, Olesen C, Schonheyder HC and Sorensen HT, "Socioeconomic factors and prescription of antibiotics in 0 - to 2 years-old Danish children", *Journal of Antimicrobial Chemotherapy*, 51, 3, 683-689, 2003.

Trap B and Hansen EH, "Cotrimoxazole prescribing by dispensing and non-dispensing doctors: do they differ in rationality?", *Tropical Medicine and International Health*, 7, 10, 878-885, 2002.

Trap B and Hansen EH, "Treatment of upper respiratory tract infections - a comparative study of dispensing and non-dispensing doctors", *Journal of Clinical Pharmacy and Therapeutics*, 27, 289-298, 2003.

Werneck GL, Guilherme L, Costa CHN, Walker AM, David JR, Wand M and Maguire JH,

“The urban spread of visceral leishmaniasis: clues from spatial analysis”, *Epidemiology*, 13, 364–369, 2002.

Windmeijer F, de Laat E, Douven R and Mot E, “Pharmaceutical promotion and GP prescription behaviour”, *Health Economics*, 15, 5–18, 2006.

Infection	Prescription	Cost of different treatment's strategies
$v$	$NA$	$\alpha w_j + td_j$
$v$	$A$	$\alpha w_j + z + td_j$
$b$	$A$	$\alpha w_j + z + td_j$
$b$	$NA+A$	$2(\alpha w_j + td_j) + z$

Table 1: The total cost of treatment depends upon doctor's prescription strategy ( $A$ =antibiotics,  $NA$ =antipyretic/anti-inflammatory only) and the type of patient's infection ( $b$ =bacterial,  $v$ =viral).

Variable	Description	Mean	Std dev.
$DID$	Defined daily doses per 1000 inhabitants	11.714	13.061
$Y$	Income per capita defined in CHF	23465	6849.4
$POP_1$	Proportion of 0-14 in total population	0.1658	0.0243
$POP_2$	Proportion of 15-25 in total population	0.1247	0.0173
$POP_3$	Proportion of 26-59 in total population	0.4956	0.0314
$POP_4$	Proportion of 60-74 in total population	0.1363	0.0213
$POP_5$	Proportion of over 74 in total population	0.0776	0.0190
$DENPOP$	Density of population		
$INF$	Incidence of common gastrointestinal infections (salmonella and campylobacter) in 100000 inhabitants	114.69	22.580
$DPHY$	Density of physicians for 100000 inhabitants	565.21	1052.5
$DPHA$	Density of pharmacies for 100000 inhabitants	35.098	39.112
$PA$	Price of a defined daily dose	3.7112	0.3113
$PC$	Price of GP consultations	0.9074	0.0526
$DBOR$	Whether or not the area borders other countries	0.125	0.0107
$DLAT$	Whether an area has a Latin (French and Italian) or a German culture	0.4375	0.0160
$DHOS$	Whether or not there is at least one hospital in the area	0.7417	0.0141
$NOSELF$	Whether or not there are no self-dispensing practices in the area	0.4083	0.0159
$SELF$	Whether or not there is a majority of self-dispensing practices in the area	0.2333	0.0137
$DISP$	% of dispensing practices across all practices in the area	0.2187	0.0100

Table 2: Variables notation and summary statistics.

	2 <sup>nd</sup> quarter			3 <sup>rd</sup> quarter			4 <sup>th</sup> quarter		
	Coefficients	St. Err.	p-value	Coefficients	St. Err.	p-value	Coefficients	St. Err.	p-value
Obs.		240			240			240	
Variance ratio		0.954			0.934			0.760	
Squared corr.		0.729			0.722			0.747	
Log likelihood		-3.177121			-0.795329			-17.235547	
Covariates	Coefficients	St. Err.	p-value	Coefficients	St. Err.	p-value	Coefficients	St. Err.	p-value
Constant	0.025063	0.039793	0.529	0.035704	0.055561	0.520	-2.189344	1.3796	0.113
Y	0.104283	0.089536	0.244	0.030359	0.090055	0.736	0.232004	0.108340	0.032
POP <sub>1</sub>	0.862084	0.282781	0.002	0.869233	0.286873	0.002	0.769758	0.260747	0.003
POP <sub>2</sub>	-0.075681	0.219118	0.730	-0.248296	0.227236	0.275	-0.337462	0.225707	0.135
POP <sub>4</sub>	0.275579	0.193988	0.155	0.183485	0.203941	0.368	0.054526	0.197749	0.783
POP <sub>5</sub>	-0.205226	0.114013	0.072	-0.237162	0.121334	0.051	-0.307096	0.113538	0.007
DENPOP	0.02825	0.019945	0.157	0.006876	0.021142	0.745	0.001577	0.020474	0.939
INF	0.009430	0.054035	0.861	-0.027550	0.052992	0.603	0.034697	0.037104	0.350
DPHY	0.081723	0.045586	0.073	0.089302	0.043706	0.041	0.119256	0.047785	0.013
DPHA	0.791959	0.080945	0.000	0.767025	0.091366	0.000	0.627884	0.072525	0.000
PA	-0.701689	0.265306	0.008	-0.300469	0.282160	0.287	-0.639604	0.252796	0.011
PC	0.355685	0.503174	0.480	0.359258	0.490390	0.464	-0.127843	0.345057	0.711
DBOR	-0.007196	0.051484	0.889	0.022529	0.049383	0.648	0.032017	0.054751	0.559
DLAT	-0.039357	0.087315	0.652	-0.111623	0.085674	0.193	0.030735	0.074830	0.681
DHOSP	0.019314	0.057979	0.739	0.017028	0.056783	0.764	0.035459	0.061394	0.564
NOSELF	0.004890	0.056341	0.931	-0.004873	0.049167	0.921	-0.032209	0.051060	0.528
SELF	0.485011	0.077254	0.000	0.422617	0.076491	0.000	0.289290	0.063419	0.000
$\lambda$	0.143424	0.025927	0.000	0.127707	0.042673	0.003	-0.002512	0.005282	0.634
Wald test of $\lambda = 0$		$\chi^2 = 30.601$	0.000		$\chi^2 = 8.956$	0.003		$\chi^2 = 0.226$	0.634
Lagrange multiplier test of $\lambda = 0$		$\chi^2 = 7.682$	0.006		$\chi^2 = 3.124$	0.077		$\chi^2 = 1.797$	0.180

Table 3: Parameter estimates of the spatial-error model for the three quarters.

	2 <sup>nd</sup> quarter			3 <sup>rd</sup> quarter			4 <sup>th</sup> quarter		
	Coefficients	St. Err.	p-value	Coefficients	St. Err.	p-value	Coefficients	St. Err.	p-value
Obs.		1.451780	0.476	-0.697993	1.455417	0.632	-2.096988	1.497989	0.163
R-squared	0.7458		0.158	0.088959	0.110968	0.424	0.225711	0.116299	0.054
F Stat.	22.55		0.008	0.663576	0.264107	0.013	0.775244	0.273841	0.005
Covariates			0.317	-0.321673	0.246728	0.194	-0.354219	0.238330	0.139
Constant	-1.036838	1.451780	0.936	-0.069425	0.199029	0.728	0.058533	0.213512	0.784
Y	0.165760	0.116904	0.072	-0.211423	0.113166	0.063	-0.313230	0.121137	0.010
POP <sub>1</sub>	0.696699	0.261851	0.411	-0.010316	0.022927	0.653	0.001251	0.021806	0.954
POP <sub>2</sub>	-0.236696	0.236125	0.563	-0.000792	0.034892	0.982	0.032490	0.039347	0.410
POP <sub>4</sub>	0.016580	0.204912	0.029	0.115851	0.045521	0.012	0.117821	0.048587	0.016
POP <sub>5</sub>	-0.207942	0.115205	0.000	0.635084	0.074444	0.000	0.624532	0.073639	0.000
DENPOP	0.182476	0.022173	0.002	-0.694598	0.224956	0.002	-0.643670	0.262394	0.015
INF	0.020252	0.034989	0.969	0.091636	0.380436	0.810	-0.098607	0.362719	0.786
DPHY	0.107087	0.048707	0.633	0.016274	0.048257	0.736	0.027422	0.056933	0.631
DPHA	0.633325	0.074554	0.829	-0.056056	0.072148	0.438	0.028871	0.077039	0.708
PA	-0.897140	0.279231	0.691	0.017570	0.061620	0.776	0.035697	0.063605	0.575
PC	-0.015728	0.398017	0.452	-0.029875	0.048668	0.540	-0.034024	0.053608	0.526
DBOR	-0.025069	0.052498	0.000	0.326651	0.064502	0.000	0.289149	0.065879	0.000
DLAT	0.016691	0.077243							
DHOSP	0.025764	0.064625							
NOSELF	-0.042663	0.056681							
SELF	0.336600	0.066311							

Table 4: Parameter estimates of OLS regressions for the three quarters.