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An Equilibrium Model Estimated on Pharmaceutical Data

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Abstract The purpose of this paper is to estimate patients' and doctors' responses to prices when making a choice between brand name products and generics. We account for the response of pharmacies to government regulation and to prices set by brand name producers. The data from the Norwegian Prescription Database are unique in the sense that we observe prices set by pharmacies as well as by producers. Our results confirm that estimating only the demand side yields biased estimates of consumers' price responses. We find much stronger price responses when demand and supply are jointly estimated.

Introduction

One important problem with estimating the demand for pharmaceuticals on microdata is that quality attributes of the product (both observed and unobserved) may be correlated with the price. These quality attributes are most likely priced out in the markets by the producers. Since the papers by Berry (1994) and Berry et al. (1995) the

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standard method in estimating demand on microdata has been to apply an algorithm proposed in these two papers. Basically, the endogeneity problem is controlled for using instrument variables. However, identifying suitable instruments is not an easy task. Recent examples in this tradition and related to demand for pharmaceuticals are Aricidiacono et al. (2013) and Granlund (2010). More recent papers using demand data only to estimate how prices affect demand are Yeung et al. (2016), who use natural experiment data, and Skipper and Vejlin (2015), who focus on how prices affect the choice between generics and brand-name drugs.

Below we estimate patients' and doctors' responses to prices when making a choice between a brand-name product and its generics. We consider how pharmacies respond to government regulation and to prices set by brand-name producers. In contrast to previous studies, we use aggregate data. In this method, demand is represented by market shares derived from discrete choices in micro, with prices of all relevant pharmaceutical products as explanatory variables. However, when using aggregate data, we are facing endogeneity problems. If we do a regression of demand against prices, we ignore that prices may depend on demand. A straightforward demand analysis may bias our estimates of price responses.

Instead of applying an instrumental variable approach, we estimate jointly the demand side and the price equations following from the prices setting of producers of brand-name products and pharmacies, given the government regulation of brand-name retail prices. In the modelling of the price setting among brand-name producers, we assume that they consider the responses by pharmacies with respect to their sales and price setting of generics versus brand-name products. We thus estimate an oligopoly model where market shares are derived from underlying discrete choice demand. Examples of this theoretical construct are discussed in Anderson et al. (1992) and in Schweitzer and Lu (2018) who are using the analytical framework of industrial organization in the analysis of the pharmaceutical markets.

The econometric approach to estimate equilibrium models was first presented in Haavelmo (1943, 1944), for which he was awarded a Nobel Prize in economics in 1989. A recent example of estimating an equilibrium model on pharmaceutical data is Dalen et al. (2014). In this study, we model the pricing behaviour of the producers of pharmaceuticals, not only the pricing behaviour of pharmacies. To include this pricing behaviour in the model, we observe the prices set by manufacturers.

The two drugs we are analysing are two best-sellers in the Norwegian market. The first, an antidepressant, is used to treat major depression, obsessive-compulsive disorder, panic disorder, social anxiety, post-traumatic stress and generalized anxiety disorder in adult outpatients. The second drug is an anti-hypertensive used in the treatment of angina pectoris.

It should be noted that since 2001, the pharmacies in Norway are almost entirely owned by international firms that also act as wholesalers. In the period analysed here, there were three pharmacy chains in Norway. The regulatory authority related to the pharmaceutical sector in Norway is the Norwegian Ministry of Health and Social Affairs. The Ministry, and its agency (Norwegian Medicines Agency), control the entry of new drugs, wholesale prices, and retail margins. The manufacturer price is not regulated.[1]

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[1] Brekke et al. (2012) for details of market structure and regulation in Nordic countries, and Vogler (2012) for an overview of pharmaceutical pricing and market regulation in 29 European countries, including Norway.

During the last decades there have been several policy initiatives by the Norwegian government to foster competition after patent expiration. Starting in 1987, doctors were encouraged to prescribe the cheapest available versions of a drug. In 1991, this relatively loose regulation was replaced by a law that instructed doctors to prescribe the cheapest available generic drug. Doctors could still prescribe a more expensive brand-name version, as long as a medical reason for this could be provided. In this period, generic competition was entirely based on the prescription-choice of the doctor. The pharmacy was required to dispense the exact product name written on the prescription. This changed in March 2001, when pharmacies were allowed to substitute a branded drug for a generic, independent of the product name prescribed by the doctor. Being permitted to intervene between the physician and the patient, the pharmacies now got an active role in the market for generics. The doctor can still guard against substitution, but this requires an explicit reservation to be added to the prescription note (called an active substitution method).

In Norway, the physicians objected substitution on 5.2% of prescriptions in 2005, and on 4.5% in 2006 (Brekke et al. 2012). Even without a reservation by the physician, the patient may insist on the branded drug, in which case the pharmacy is obligated to hand out the brand-name drug. In this case, the insurance scheme does not cover the price difference between the branded drug and the reference price. The difference has to be paid by the patient himself. In 2005, the patients refused to substitute on 4% of the prescriptions (4.3% in 2006). These come in addition to the reservations made by the physicians, bringing the total number of refusals to substitute close to an average of 10% of all prescriptions. The two drugs we analyse here are all approved for reimbursement for part of the expenses by the social insurance scheme. Patents for both drugs have expired, so patients/doctor can freely choose between brand-name drugs and generics.

In the period considered here, there was a price cap on brand name products. Under this regulatory scheme, the regulator sets a maximum price level defined by the lowest observed prices in a selection of European countries. This price cap is first set when the brand-name drug enters the market. After patent expiration, generic drugs are given the exact same price cap, which only falls if generic competition triggers price reductions in the reference countries. However, competition from generics (made possible by generic substitution) was supposed to lower prices below the price cap.

In most studies of pharmaceuticals, information about prices at the different levels of the market has been lacking. One example is Coscelli (2000), who was able to reveal the habit behaviour claimed by Hellerstein (1998). Another is Lundin (2000), who had access to retail prices (only) and found support for habit persistence among doctors and patients. However, the results indicated that these are affected by the price differences, especially the share of price differences covered by the patient. If the price differences between generic and brand-name increases, the doctor becomes more inclined to prescribe a generic version.

The data we use here are quarterly register data for 2004–2008. We have access to unique price data that give the prices set by the brand-name producers as well as by the retailers and wholesalers. Our results indeed indicate that if only the demand side is estimated, the estimates of price responses are biased. It should be noted that what we analyse here are products which, from a medical point of view, are perfect substitutes. The chemical substance in the brand-name products and the generics are identical. We should thus expect the demand elasticities to be numerically high.

Demand and Pricesetting

Pharmaceutical products can be specified according to chemical substance. One specific substance, identified by anatomical therapeutic chemical classification system (ATC code) corresponds to one market. In each market the patient/doctors can choose between the brand-name product and generics and between three pharmacy chains. The model therefore deals with the choice of brand-name products vs generic substitution.

Demand Side

Choice of Drugs, Given the Chain

Let U_{ncd} be the utility for patient/doctor n of using drug d bought in retailer chain c, where $d = B,G$ and $c = 1,2,3$. B stands for brand-name product and G for generics, of which there can be many different drugs but with the same chemical substance. Let P_{cd} be the price of the drug d in retailer chain c. We will assume that

$$U_{ncd} = a_{cd} + bP_{cd} + \varepsilon_{ncd} \tag{1}$$

Here a_{cd} and b (<0) are constants. ε_{ncd} is assumed to be extreme value distributed with zero expectation and unit variance. The latter means that the coefficients a_{cd} and b are scaled with the standard deviation of the extreme value distributed taste shifter. For each chain we get the following choice probabilities, denoted Y_{cd}.

$$Y_{cd} = \frac{exp(v_{cd})}{\sum\limits_{s=B,G} exp(v_{cs})}; c = 1, 2, 3; d = B, G \tag{2}$$

where

$$v_{cd} = a_{cd} + bP_{cd} \tag{3}$$

We note that the deterministic part of the random utility function in (1), v_{cd}, does not depend on individual characteristics.

Choice of Chain

Let Z_c denote the probability that the individuals choose chain c, $c = 1,2,3$, and it is given by

$$Z_c = \frac{exp(I_c)}{\sum\limits_{r=1}^{3} exp(I_r)} = \frac{\sum\limits_{j=B,G} exp(v_{cj})}{\sum\limits_{r=1}^{3} \sum\limits_{j=B,G} exp(v_{rj})}; \quad c = 1, 2, 3 \tag{4}$$

$$I_c = ln \sum_{j=B,G} \left(exp\left(v_{cj}\right)\right) \tag{5}$$

I_c is the expected value of the maximum of utility related to the choice of drugs in chain c, also called inclusive value (Train 2009). Z_c is the ratio of the expected value of the maximum utility of choosing drugs in chain c to the sum of the expected value of maximum utility across the three chains.

Market Shares for Drugs

The unconditional probability of choosing a generic or a brand-name drug is then given by the product of Y_{cd} and Z_c, which here will be denoted X_{cd}:

$$X_{cd} = Y_{cd}Z_c = \frac{exp(v_{cd})}{\sum_{r=1}^{3} \sum_{j=B,G} exp\left(v_{rj}\right)}; c = 1, 2, 3, d = B, G \tag{6}$$

Note that when the agents choose between generics/brand and chains, $X_{cG} + X_{cB}$ is not equal to one, but $\sum_{r=1}^{3} \sum_{j=B,G} X_{rj} = 1$.

The simplification that the deterministic parts of the utility function in (1) do not depend on individual characteristics implies that empirical parallels to the aggregate demand probabilities in (6) are market shares. Thus, X_{cd} is the share chain c has in market for drug d. In the empirical part we will come back to how we deal with the heterogeneity in the market share equations.

Supply Side: a Non-cooperative Game

There are three stages in this game. In the first stage the brand-name producer sets the price. In doing so, he utilizes the demand structure and the price setting of the generic producers and the retailers. In the second stage the generic producers set their prices and in third stage the retailer set his prices, given the prices set by the generic producers and brand-name producer (see Fig. 1).

As common in these games, we start at the end. The model we employ combines a demand model derived from logit probabilities and monopolistic price setting (Anderson et al. 1992, chapter 7, for a theoretical outline of similar models).

Pricing Decisions of Three Retailer/Wholesalers Chains

For expository reason we specify one supplier of generics. The expected profit of the chain c is given by

$$\pi_c = (P_{cB} - q_{cB})X_{cB} + (P_{cG} - q_{cG})X_{cG}; c = 1, 2, 3 \tag{7}$$

As mentioned above, in the Norwegian market the retailer and the wholesaler are vertically integrated. Here q_{cB} is what retailer c thus has to pay the producer for the
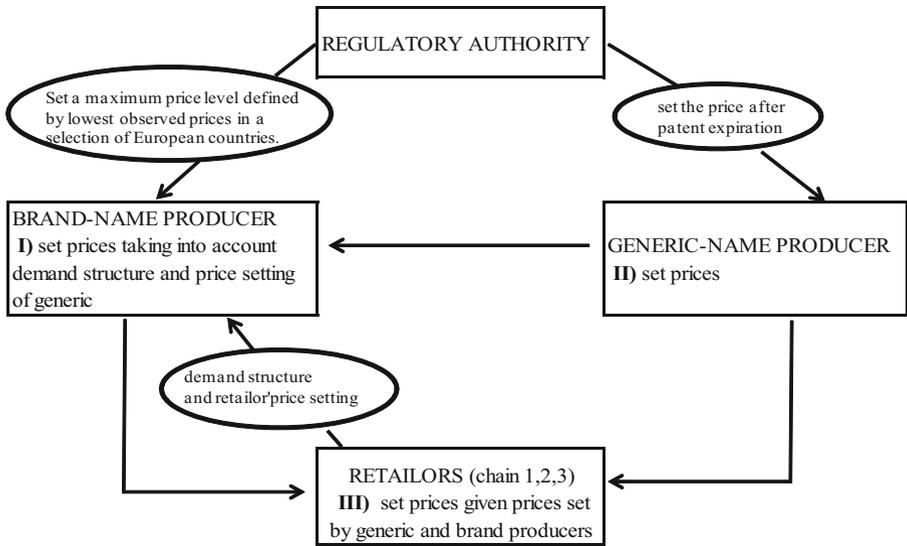
Fig. 1 Stage representation of the game

brand-name product, while q_{cG} is what he has to pay the producer for the generic product.

In the expression above we have set the number of potential users equal to 1, which is a normalisation without any implications for the results. Thus, the two market shares given in Eq. (6), X_{cB} and X_{cG}, equal the expected volume of brand-name and generics sold by chain c. In Norway brand-name prices are regulated with a price-cap:

$$P_{cB} = \overline{P}_{cB} \tag{8}$$

In accordance with the situation in the Norwegian market, we assume that the price cap is binding.

We assume that the retailer/wholesaler set a price of the generics that maximize profits. Maximizing expected profit with respect to the price of generics yields the following first order condition:

$$\frac{\partial \pi_c}{\partial P_{cG}} = \left(\overline{P}_{cB} - q_{cB}\right)\frac{\partial X_{cB}}{\partial P_{cG}} + X_{cG} + (P_{cG} - q_{cG})\frac{\partial X_{cg}}{\partial P_{cG}} = 0 \quad for\, c = 1, 2, 3 \tag{9}$$

Given the structure of the market shares that we assume that the retailer knows, we then get the following price setting of generics:

$$P_{cG} = q_{cG} + \frac{1}{(-b)(1 - X_{cG})} + \frac{X_{cB}}{1 - X_{cG}}\left(\overline{P}_{cB} - q_{cB}\right); c = 1, 2, 3 \tag{10}$$

The first element on the right-hand side, q_{cG}, is the direct cost to the retailer chain c of buying generics. The second element is the standard mark-up in these types of models (see Anderson et al. 1992), while the third element captures the opportunity cost related to the fact that the retailer can sell brand-name products instead of generics.

Pricing Decisions of the Generic Producers

Without introducing too strong of assumptions, we assume that the prices of generics are set equal to marginal cost, k_G. The marginal cost is not observed but will be estimated together with the other unknown parameters of the model.

$$q_{cG} = k_G \tag{11}$$

Pricing Decision of the Brand Producer

The expected profit of the brand producer is given by

$$\pi_B = \sum_{c=1,2,3} (q_{cB} - k_B) X_{cB} \tag{12}$$

In maximizing expected profit with respect to the price, q_{cB}, the brand-name producer considers how the retailers set their price of generics in response to an increase in the producers' price of brand-name product. According to (6), X_{cB} depends on P_{cG}. From (6) and (10), and after some time-consuming but straight- forward calculations, we find that

$$\frac{\partial P_{cG}}{\partial q_{cB}} = -X_{cB} < 0 \tag{13}$$

Thus, if the brand-name producer increases his price, the retailer lowers the price of generics in order to shift the sale in pharmacies towards more generics. The marginal cost is k_B. The first order condition becomes:

$$q_{cB} = k_B + \frac{1}{(-b) X_{cG} X_{cB}} \tag{14}$$

Most likely, the marginal cost of producing the drug is low and equal across generics and brand-name producers. Hence, we set $k_G = k_B = k$.

The Econometric Model

To take the market shares and the pricing equations to data, requires that we specify how unobserved variables are coming into the model. First, we let the brand-name product sold by chain no 1 to be the reference case. Dividing through the markets shares in (6) by X_{1B}, we get

$$\begin{cases} \dfrac{X_{cB}}{X_{1B}} = \dfrac{\exp(v_{cB})}{\exp(v_{1B})} = \exp(v_{cB} - v_{1B}); c = 2, 3 \\[2mm] \dfrac{X_{cG}}{X_{1B}} = \dfrac{\exp(v_{cG})}{\exp(v_{1B})} = \exp(v_{cG} - v_{1B}); c = 1, 2, 3, \end{cases} \tag{15}$$

Taking logs and applying (3) we get

$$ln\frac{X_{cB}}{X_{1B}} = (a_{cB}-a_{1B}) + b\left(P_{cB}-\overline{P}_{1B}\right); c = 2,3$$
$$ln\frac{X_{cG}}{X_{1B}} = (a_{cG}-a_{1B}) + b\left(P_{cG}-\overline{P}_{1B}\right); c = 1,2,3 \tag{16}$$

The term to the left, the log of the relative market shares, is the log-odds ratio, with brand-name drug sold by chain 1 as the reference case. We observe from $\sum\limits_{r=1}^{3} \sum\limits_{j=B,G} X_{rj}$ = 1 that

$$X_{1B} = 1- \sum_{r=2,3} X_{rB} - \sum_{r=1,2,3} X_{rG} \tag{17}$$

We add a stochastic term to the log-odds ratios, denoted ε_{cd}. The justification for this is that there may be unobserved variables affecting the choices. With a reference to the central limit theorem we assume that these stochastic terms are normally distributed with zero expectation and standard deviation σ_{cd}.

The demand model with random parts added is

$$ln\frac{X_{cB}}{X_{1B}} = (a_{cB}-a_{1B}) + b\left(P_{cB}-\overline{P}_{1B}\right) + \varepsilon_{cB}; c = 2,3$$
$$ln\frac{X_{cG}}{X_{1B}} = (a_{cG}-a_{1B}) + b\left(P_{cG}-\overline{P}_{1B}\right) + \varepsilon_{cG}; c = 1,2,3 \tag{18}$$

Altogether there are two equations covering the log-odds ratio for brand-name product, i.e. sold by chain 2 and 3 and three equations for the log-odds ratios of generics, i.e. sold by all three chains.

Now let

$$\begin{cases} D_{cBt} = ln\frac{X_{cBt}}{X_{1Bt}} - \alpha_{cB} - b\left(P_{cBt}-\overline{P}_{1Bt}\right) = \varepsilon_{cBt}; c = 2,3,; t = 1,2,,,T \\ D_{cGt} = ln\frac{X_{cGt}}{X_{1Bt}} - \alpha_{cG} - b\left(P_{cGt}-\overline{P}_{1Bt}\right) = \varepsilon_{cGt}; c = 1,2,3,; t = 1,2,,,T \end{cases} \tag{19}$$

Here we have added the subscript t. The model will be estimated on quarterly data and with a total of T quarters. Moreover, $\alpha_{cd} = a_{cd}-a_{1B}$. Note that D_{cdt} depends on observed markets shares and observed prices, as well as on the unknown coefficients α_{cd} and b. The latter coefficient captures the effect of price on demand for drugs. Now let

$$\begin{cases} D_{cBt}\left(X_{cBt}, X_{1Bt}, \left(P_{cdt}-\overline{P}_{1Bt}\right); \alpha_{cB}, b\right) = ln\frac{X_{cBt}}{X_{1Bt}} \alpha_{cB} - b\left(P_{cBt}-\overline{P}_{1Bt}\right), c=2,3,; t=1,2,,,T \\ D_{cGt}\left(X_{cGt}, X_{1Bt}, \left(P_{cdt}-\overline{P}_{1Bt}\right); \alpha_{cG}, b\right) = ln\frac{X_{cGt}}{X_{1Bt}} - \alpha_{cG} - b\left(P_{cGt}-\overline{P}_{1Bt}\right), c=1,2,3,; t=1,2,,,T \end{cases} \tag{20}$$

Dividing through (19) with the standard deviation σ_{cd}, using (20), we get

$$\begin{cases} \dfrac{D_{cBt}\left(X_{cBt}, X_{1Bt}, \left(P_{cBt} - \overline{P}_{1Bt}\right); \alpha_{cB}, b\right)}{\alpha_{cd}} = \dfrac{\varepsilon_{cBt}}{\sigma_{cB}}; c=2,3,; t=1,2,,,T \\[3mm] \dfrac{D_{cGt}\left(X_{cGt}, X_{1Bt}, \left(P_{cGt} - \overline{P}_{1Bt}\right); \alpha_{cG}, b\right)}{\sigma_{cd}} = \dfrac{\varepsilon_{cdt}}{\sigma_{cd}}; c=1,2,3,; t=1,2,,,T \end{cases} \quad (21)$$

The random term to the right is then a standard normal distributed random term with zero expectation and unit variance. Let f(.) be the standard normal density function. For a given drug, we then have the following joint probability function for the sample we observe, based on demand data only:

$$L_D = \prod_{t=1}^{T} \prod_{c=2}^{3} \frac{1}{\sigma_{cB}} f\left(D_{cBt} \frac{\left(X_{cBt}, X_{1Bt}, \left(P_{cBt} - \overline{P}_{1Bt}\right); \alpha_{cB}, b\right)}{\sigma_{cB}}\right) \prod_{c=1}^{3} \frac{1}{\sigma_{cG}} f\left(D_{cGt} \frac{\left(X_{cGt}, X_{1Bt}, \left(P_{cGt} - \overline{P}_{1Bt}\right); \alpha_{cG}, b\right)}{\sigma_{cG}}\right)$$

$$(22)$$

L_D is the likelihood for the sample (of market shares) we observe and we estimate the unknown coefficients (α_{cd}, b, σ_{cd}) by maximizing this likelihood, or rather the log of this likelihood, with respect to the unknown coefficients. In doing so, we let our theory has the highest possible chance to explain data. This approach we call demand side estimates, DSE.

We now turn to the specification of the econometric model when the demand side and pricing behaviour of retailer/wholesaler and producers of drugs are jointly estimated. Adding error terms to the pricing equations, and applying (11), we get

$$P_{cGt} = k + \frac{1}{(-b)(1 - X_{cGt})} + \frac{X_{cBt}}{1 - X_{cGt}}\left(\overline{P}_{cBt} - q_{cBt}\right) + \eta_{cGt}; c = 1, 2, 3, t = 1, 2, , , T \quad (23)$$

Similar to above, we assume η_{cGt} to be normally distributed with zero expectation and standard deviation τ_{cG}. Now let

$$S_{cGt}(X_{cBt}, X_{cGt}, P_{cGt}, q_{cBt}; k, b) = P_{cGt} - k - \frac{1}{(-b)(1 - X_{cGt})} - \frac{X_{cBt}}{1 - X_{cGt}}\left(\overline{P}_{cBt} - q_{cBt}\right); c$$

$$= 1, 2, 3, t = 1, 2, , , T \quad (24)$$

From (23) and (24), and dividing through with τ_{cG}, we get,

$$\frac{S_{cGt}(X_{cBt}, X_{cGt}, P_{cGt}, q_{cBt}; k, b)}{\tau_{cG}} = \frac{\eta_{cGt}}{\tau_{cG}}; c = 1, 2, 3; t = 1, 2, , , T \quad (25)$$

For the prices set by the producers which chain c has to pay, we have

$$q_{cBt} = k + \frac{1}{(-b)X_{cGt}X_{cBt}} + \eta_{cBt} \quad (26)$$

Again, we let

$$S_{cBt}(X_{cGt}, X_{cBt}, q_{cBt}; k, b) = q_{cBt} - k + \frac{1}{(-b)X_{cGt}X_{cBt}}; c = 1, 2, 3; t = 1, 2, , , T \quad (27)$$

Then from (26) and (27) we get

$$\frac{S_{cBt}(X_{cGt}, X_{cBt}, q_{cBt}; k, b)}{\tau_{cB}} = \frac{\eta_{cBt}}{\tau_{cB}}; c = 1, 2, 3; t = 1, 2, , , T \quad (28)$$

Let L_S denote the joint probability covering the pricing decisions:

$$L_S = \prod_{t=1}^{T} \prod_{c=1}^{3} \frac{1}{\tau_{cG}} f\left(\frac{S_{cGt}(X_{cBt}, X_{cGt}, P_{cGt}, q_{cBt}; k, b)}{\tau_{cG}} \right.$$

$$\left. \times \prod_{c=1}^{3} \frac{1}{\tau_{cBt}} f\left(\frac{S_{cBt}(X_{cGt}, X_{cBt}, q_{cBt}; k, b)}{\tau_{cB}} \right) \right) \quad (29)$$

Altogether we have 5 demand equations (in terms of market shares), 3 equations for the prices of generics set by the pharmacies and 3 equation for the prices on brand-name products set by the producers. We thus have a total of 11 equations. Note that demand depend on all prices in pharmacies, on brand-name products as well as on generics. Prices of generics set by pharmacies depend on the price-caps on brand and the producer prices of brand-name products.

The joint probability covering the demand and pricing decisions observed in our sample is given by the product $L_D L_S$. Before we proceed to the empirical part of the paper we have to do one more thing.

At any point in, time the observed dependent variables are.

$(X_{2Bt}, X_{3Bt}, X_{1Gt}, X_{2Gt}, X_{3Gt}, P_{1Gt}, P_{2Gt}, P_{3Gt}, q_{1Bt}, q_{2Bt}, q_{3Bt})$.

The market share for X_{1Bt} follows from Eq. (17). Because there are the following 11 unobserved normally distributed random variables in the model, $(\varepsilon_{2Bt}, \varepsilon_{3Bt}, \varepsilon_{1Gt}, \varepsilon_{2Gt}, \varepsilon_{3Gt}, \eta_{1Gt}, \eta_{2Gt}, \eta_{3Gt}, \eta_{1Bt}, \eta_{2Bt}, \eta_{3Bt})$, the observed dependent variables will also be random and normally distributed variables. What is not so common in econometrics, but common in statistics and also discussed at length in Haavelmo (1944), is to apply a Jacobian transformation. This transformation means that we make a bridge from the distribution of the unobserved random variables present in the model to the distribution of the observed dependent variables.

To clarify what this transformation is, we give an example. Let $F(\varepsilon^*)$ be the cumulative distribution for the random variable ε, evaluated in the point ε^* and let $\varepsilon = g(x)$. Then taking the differentials we get $d\varepsilon f(\varepsilon^*) = f(g(x^*))g'(x^*)dx$. Here $f(.)$ is the derivative of $F(.)$, i.e. the probability density function, and $g'(.)$ is the derivative of $g(.)$.

In our case we have 11 equations. In each equation we have one unobserved random variable and a varying number of observed dependent variables. For example, in equation number 1 we have

$$\varepsilon_{c2Bt} = \ln\frac{X_{2Bt}}{X_{1Bt}} - \alpha_{cB} - b\left(P_{2Bt} - \overline{P}_{1Bt}\right) = \ln X_{2Bt} - \ln\left(1 - \sum_{r=2,3} X_{rBt} - \sum_{r=1,2,3} X_{rGt}\right) - \alpha_{cB} - b\left(P_{2Bt} - \overline{P}_{1Bt}\right)$$

Taking the derivatives to all 11 observed variables, starting with X_{2Bt} and ending with q_{3Bt}, we get the following line of derivatives:

$$X^{-1}_{1Bit} + X^{-1}_{2Bit}, X^{-1}_{1Bit}, X^{-1}_{1Bit}, X^{-1}_{1Bit}, X^{-1}_{1Bit}, 0, 0, 0, 0, 0, 0.$$

Now let, J_t denote the matrix of the derivatives of all 11 equation, and let $|J_t|$ denote the numerical value of the determinant, called the Jacobian determinant.

$$J_t = \begin{pmatrix} X^{-1}_{1Bt} + X^{-1}_{2Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bi}, 0, 0, 0, 0, 0, 0 \\ X^{-1}_{1Bt}, X^{-1}_{1Bt} + X^{-1}_{3Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, 0, 0, 0, 0, 0, 0 \\ X^{-1}_{1Bt}, X^{-1}_{1Bi}, X^{-1}_{1Bt} + X^{-1}_{1Gi}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, -b, 0, 0, 0, 0, 0 \\ X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt} + X^{-1}_{2Gt}, X^{-1}_{1Bt}, 0, -b, 0, 0, 0, 0 \\ X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt}, X^{-1}_{1Bt} + X^{-1}_{3Gt}, 0, 0, -b, 0, 0, 0 \\ 0, 0, -b^{-1}(1-X_{1Gt})^{-2}\left(\overline{P}_{1Bt} - q_{1Bt}\right), 0, 0, 1, 0, 0, -b^{-1}(1-X_{G1t})^{-1}, 0, 0 \\ 0, 0, 0, -b^{-1}(1-X_{2Gt})^{-2}\left(\overline{P}_{2Bt} - q_{2Bt}\right), 0, 0, 1, 0, 0, -b^{-1}(1-X_{G2t})^{-1}, 0 \\ 0, 0, 0, 0, -b^{-1}(1-X_{3Gt})^{-2}\left(\overline{P}_{3Bt} - q_{3Bt}\right), 0, 0, 1, 0, 0, -b^{-1}(1-X_{G3t})^{-1} \\ b^{-1}X^{-1}_{1Gt}X^{-2}_{1Bt}, b^{-1}X^{-1}_{1Gt}X^{-2}_{1Bt}, b^{-1}X^{-1}_{1Gt}X^{-1}_{1Bt}(X^{-2}_{1Bt}-X^{-1}_{1Gt}), b^{-1}X^{-1}_{1Gt}X^{-2}_{1Bt}, b^{-1}X^{-1}_{1Gt}X^{-2}_{1Bt}, 0, 0, 0, 1, 0, 0 \\ -b^{-1}X^{-1}_{2Gt}X^{-2}_{2Bt}, 0, 0, -b^{-1}X^{-2}_{2Gt}X^{-1}_{2Bt}, 0, 0, 0, 0, 0, 1, 0 \\ 0, -b^{-1}X^{-1}_{3Gi}X^{-2}_{3Bi}, 0, 0, -b^{-1}X^{-2}_{3Gt}X^{-1}_{3Bt}, 0, 0, 0, 0, 0, 1 \end{pmatrix}$$

$$(30)$$

From an econometric point of view, the importance of accounting for the Jacobian transformation is that $|J_t|$ may depend on the coefficients that we like to estimate. We observe that $|J_t|$ depends on the coefficient b. Without utilizing the Jacobian transformation when estimating the model, we may get a biased estimated of b. The expanded likelihood we will use in estimating the unknown coefficients of our model is therefore

$$L(\theta; X_t, P_t, q_t) = L_D L_S |J_t| \qquad (31)$$

where

$\theta = \{b, \alpha_{2B}, \alpha_{3B}, \alpha_{1G}, \alpha_{2G}, \alpha_{3G}, \sigma_{2B}, \sigma_{3B}, \sigma_{1G}, \sigma_{2G}, \sigma_{3G}, \tau_{2B}, \tau_{3B}, \tau_{1G}, \tau_{2G}, \tau_{3G}\}$ is the vector of 13 unknown coefficients that we like to estimate and X_t, P_t, q_t are vector of our observed variables at each point in time. The functions $L_D L_S |J_t|$ and their dependency on coefficients and observed variables are given in Eqs. (22), (29) and (30). We call this approach to estimate price response market equilibrium estimates (MEE).

As mentioned above the models outlined above will be estimated on aggregated quarterly data. First, we estimate the demand side only, DSE estimates. Second, we estimate jointly the demand side and the pricing equations (i.e. the equilibrium model, MEE), and accounting for Jacobian transformation which gives the transformation from the distribution of the unobserved random variables to the distribution of the observed endogenous random variables. In both cases the unknown coefficients are estimated by maximizing the implied log-likelihood for the observed sample. We also report demand elasticities, denoted E_{cdt}, given by

$$E_{cdt} = b(1-X_{cdt})P_{cdt}; c = 1, 2, 3, d = B, G, t = 1, 2, , , T \qquad (32)$$

Data

Using quarterly data from National Prescription Data Base (Folksholseinstitutiet 2017) for the period 2004–2008, we estimate the model for two important drugs in the Norwegian market: Seroxat/Paroxetin and Amlodpin/Norvasc. Seroxat/Paroxetin is an antidepressant drug. It is used to treat major depression, obsessive-compulsive disorder, panic disorder, social anxiety, post-traumatic stress and generalized anxiety disorder in adult outpatients. Amlodpin/Norvasc is an anti-hypertensive drug used in the treatment of angina pectoris.

In the Norwegian market there were three pharmacy chains, which acted as retailers and wholesalers; Apokjeden, Holtung and NMD. Below they are named chain 1–3, not necessarily in the order mentioned here.[2]

Estimates

Tables 1 and 2 give the estimates. They are based on the maximum likelihood approach outlined above. In addition to the estimates we report asymptotically z-test.

We first observe that the coefficient attached to price is negative and highly significant both in the demand model and in the equilibrium model. The numerical value of the price coefficient is significantly higher when the equilibrium process is accounted for (MEE), relative to the result of using the demand side only, i.e. market shares, in estimating price responses (DSE). It is important to account for price formation when demand responses are estimated.

Second, the unobserved heterogeneity, as measured by the estimated standard deviations in demand and price equations, is a significant factor in explaining the observed choices. In particular, this is the case for the producer price formation for brand-name drugs. The constants, α_{cd}, are fixed effects across chains and brand-name and generics. Most of them are significantly different from zero and reflects also the heterogeneity in the demand equations.

The estimates of the marginal cost of producing generics as well as brand $(k_G = k_B = k)$, here assumed to equal the producer price of generics, are considerably lower than the retail prices of generics. This indicates a substantial margin for the generics sold by the retailers.

We have tested whether there is autocorrelation in the demand part of the equilibrium model, the MEE approach. We have applied a modified Portmanteau statistic suggested by Ljung and Box (1978), which has a larger power when the sample is finite. Given the null hypothesis is true (there are no autocorrelation), the statistic Q in Eq. (33) converges to the Chi-square distribution with m degree of freedom. In (33) m is the number of lags specified and ➔ indicates convergence in distribution to a χ^2 distribution with m degrees of freedom. $\hat{\rho}_j$ is the estimated autocorrelation for lag j.

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[2] We provide a description of the variables and summary statistics including market shares in http://folk.uio.no/steinast/supplements/An%20Equilibrium%20Model-Sum.stat.pdf

Table 1 Estimates. ATC code NO6AB05: Seroxat, Paroxetin (2004–2008)

Coefficients	Demand model (DES)		Equlibrium model (MEE)	
	Estimates	z	Estimates	z
α_{2B}	−0.1441	−0.9449	−0.3341	−1.4790
α_{3B}	0.3148	4.6985	0.3469	5.6224
α_{1G}	−0.4669	−1.5228	−0.9227	−3.1109
α_{2G}	0.1061	0.5954	−0.3638	−2.1176
α_{3G}	0.1498	0.5916	−0.3261	−1.2292
b	**−0.5503**	**−9.3748**	**−0.7495**	**−13.7271**
k			2.0257	5.9830
σ_{B2}	0.5309	4.3445	0.8227	4.5833
σ_{B3}	0.2482	4.8955	0.2284	5.2027
σ_{G1}	1.0311	5.2715	1.0062	5.2902
σ_{G2}	0.4191	5.0985	0.4251	5.0789
σ_{G3}	0.7883	5.2729	0.8645	5.2047
τ_{G1}			2.0861	5.2481
τ_{G2}			2.0485	5.2837
τ_{G3}			1.9399	5.2715
τ_{B1}			164.0017	4.9224
τ_{B2}			59.5189	4.9068
τ_{B3}			78.0807	4.9118
Log-likelihood	8.4541		53.8313	

Source: Norwegian Prescription Data Base (Folksholseinstitutiet 2017)

$$Q = n(n+2) \sum_{j=1}^{m} \frac{1}{n-j} \hat{\rho}^2(j) \rightarrow \chi_m^2 \qquad (33)$$

If the p value of Q is less than 0.05 in Table 3, then there is significant autocorrelation. As seen from the Table, there is no significant autocorrelation in the demand part of the equilibrium model. The same is also the case in the DSE approach.

Own Price Elasticities

Table 4 give the elasticities for the two drugs. In both cases the brand-name elasticities tend to be higher than the generic elasticities, which follow from the fact that the price of brand-named drugs exceeds the price of generics. Moreover, the brand-named market shares are lower than the market shares for generics in almost all periods and for all three chains. According to the formula (32) higher prices and lower market shares will contribute to higher elasticities. However, what is most important is the result that the elasticities are numerically higher when the equilibrium process is accounted for compared to when only a demand model is used in estimating the elasticities.

Table 2 Estimates. ATC code C08CA01: Amlodpin, Norvasc (2004–2008)

Coefficients	Demand model (DES)		Equlibrium model (MEE)	
	Estimates	z	Estimates	z
α_{2B}	0.1341	7.2097	0.1036	3.6608
α_{3B}	0.3028	6.9770	0.2579	4.7148
α_{1G}	0.3066	1.8787	−0.2391	−1.2363
α_{2G}	0.3029	1.2399	−0.2794	−1.0418
α_{3G}	0.8633	5.7248	0.3205	1.7231
b	**−0.7148**	**−10.4503**	**−1.0683**	**−11.0820**
k			0.4332	2.4868
σ_{B2}	0.0683	5.4206	0.1046	4.3584
σ_{B3}	0.1648	5.3856	0.2063	5.1191
σ_{G1}	0.4800	5.4157	0.4779	5.3757
σ_{G2}	0.8398	5.4746	0.8367	5.4722
σ_{G3}	0.4195	5.4129	0.4367	5.2299
τ_{G1}			0.9603	5.4254
τ_{G2}			0.7226	5.4660
τ_{G3}			1.0276	5.4313
τ_{B1}			103.3854	4.8192
τ_{B2}			75.9816	4.8869
τ_{B3}			37.7333	4.8618
Log-likelihood	56.3915		181.7330	

Source: Norwegian Prescription Data Base (Folksholseinstitutiet 2017)

Conclusions

When estimating price response based on the demand model only, the risk is that the estimates of price elasticities can be biased. Price responses could be underestimated, as demonstrated above. This will be the case if there are unobserved elements in the

Table 3 Test of autocorrelation in the estimated log-odds ratio equations in the MEE model (2004–2008)

	Portmanteau (Q) statistic	*p* value for Q
Atc code N06AB05: Seroxat,Paroxetin		
Chain 1	5.9570	0.1137
Chain 2	1.3006	0.7290
Chain 3	1.7386	0.6284
Atc code C08CA01: Amlodpin,Norvasc		
Chain 1	4.1967	0.5215
Chain 2	4.0058	0.54860
Chain 3	8.4436	0.1334

Source: Norwegian Prescription Data Base (Folksholseinstitutiet 2017)

Table 4 Own price elasticities

	Demand model						Equilibrium model					
	Brand			Generic			Brand			Generic		
N06AB05: Seroxat and Paroxetin (2004–2008)												
Chain	1	2	3	1	2	3	1	2	3	1	2	3
Mean, all periods	−3.29	−2.68	−3.34	−1.95	−1.73	−1.61	−4.48	−3.65	−4.55	−2.65	−2.36	−2.2
Last period	−1.63	−3.18	−3.05	−1.3	−0.93	−0.89	−2.22	−4.34	−4.16	−1.78	−1.26	−1.21
C08CA01: Amlodpin,Norvasc.												
Chain	1	2	3	1	2	3	1	2	3	1	2	3
Mean, all periods	−2.29	−2.2	−2.16	−1.1	−1.01	−0.92	−3.43	−3.28	−3.23	−1.64	−1.51	−1.37
Last period	−1.95	−1.96	−1.97	−0.67	−0.64	−0.54	−2.92	−2.94	−2.94	−1.01	−0.95	−0.81

Source: Norwegian Prescription Data Base (Folksholseinstitutiet 2017)

demand model that correlates with price. There are two ways of dealing with this problem: One could either employ an instrument variable approach or as done here, modelling the assumed whole data generating approach of demand and price setting. The advantage of an instrument variable approach is that it is rather straightforward to estimate the model. The disadvantage, however, is that it is hard to find quality instruments. The advantage of estimating jointly the demand and the price formation is that one avoids the search for proper instruments. The disadvantage is that it could be hard to estimate the model. But as shown here, with the software and computers available today this joint estimation of demand and price setting is manageable.

Although the estimation gives significant and reliable results, longer time series, covering periods with some regulatory shocks, may add some interesting results compared to what is found here. Another interesting next step could be to estimate the model on data from countries with a different market structure from the Norwegian oligopoly market, for instance a more competitive market. Finally, use of individual register-data will make it possible to model microeconomic behavior combined with price setting among pharmacies and producers.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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