DEMAND INDUCTION WITH A DISCRETE DISTRIBUTION OF PATIENTS

Daniele Fabbri and Chiara Monfardini*

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Abstract:

We test the "induced demand" model on cesarean section, relying on a natural experiment of proportional fee reduction of all delivery procedures. This fee change does not imply any substitution effect and allows a proper measure of the income effect. We extend the demand induction model and derive its testable implications by introducing a discrete class of patients towards which physicians can discriminate their inducement behaviour. The empirical test is performed estimating a simultaneous binary probit model in which the probability of c-section delivery depends on the type of hospital chosen and the latter is allowed to be endogenously determined.

Keywords: Induced demand, cesarean section delivery, natural experiment, simultaneous binary probit model

JEL classification: I11, I18, C35

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* Dept. of Economics, University of Bologna

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1 INTRODUCTION

Understanding the agency relationship between physician and patients is critical to the health economy. Most of the focus in the literature has been on whether physicians act as perfect agents for their patients, or if, alternatively, they can succeed in convincing their patients to act in a way that also benefits themselves, i.e. inducing demand for their services. Typically we would expect that an increase in supply would lower price, but that is not necessarily the case if physicians can induce demand. Furthermore, physicians should supply fewer services if they are paid less per service, but again, this would not be the case if demand inducement were in place. This problem is endemic to the health economy. It affects both the competitive allocation of services and, to a larger extent, health insurance markets. Once insurance is in place, physicians might induce demand on patients that are even less price-sensitive.

The "induced-demand" model, as that of McGuire and Pauly (1991), states that in the face of negative income shocks, physicians may exploit their agency relationship with patients by providing excessive care. The underlying hypothesis of such models is as follows: physicians derive utility from income and leisure, and disutility from inducing demand for unnecessary services. The disutility may arise from ethical considerations or from reputation effects. In this context, when income is tailored to specific procedures, physicians will exploit their agency relation with patients to perform more remunerative procedures if the marginal benefit of a specific procedure outweighs the associated marginal costs.

Income shocks may arise from different sources. A first source is variations in the physician/population density across areas: increased density lowers the income of existing stock of physicians, and it will lead to increased utilization of medical procedures in an inducement-type model. Income shocks may also emerge as the consequence of an exogenous change in demand due to epidemiological shifts, evolution of needs, variation in tastes. However the most common source is variation in fees paid to physicians, generally by government payers. This type of income shocks is generally accompanied by substitution as well as income effects: reducing the fees of the more remunerative procedure might lead to both an increase (income effect) and a reduction (substitution effect) in its adoption. The inducement model has traditionally been tested by assessing how these three alternative changes in the environment facing physicians affect the utilization of medical procedures.

Each of these testing strategies faces important problems. Studies that use physician density changes to proxy for income shocks [see Fuchs (1978) or Cromwell and Mitchell (1986)] suffer from omitted variables problems.[1] An area may feature both higher procedure utilization and more physicians, regardless of the extent of demand inducement, because of the lack of control for variable correlated with taste for medical interventions, like the average coinsurance rate in the area. Concerning demand changes, these are quite difficult to measure. Moreover they take place with a very slow pace thus leading to problems of control for concomitant changes. Finally, fee changes[2] cannot properly identify supply responses because, as far as substitution and income effects go in opposite directions, there may be inducement, but these two effects may simply be cancelling; moreover, there may be a concurrent demand response to changing prices.

A large body of evidence and econometric work is available upon demand induction in surgical procedures. In this context cesarean section is probably the most studied procedure. C-section is an increasingly adopted technology for birth; it is more expensive and therefore more generously reimbursed than natural delivery; it is clinically less appropriate than natural delivery and therefore ethical and professional rewards do matter in this context.

Tussing and Wojotowycz (1992), examining New York data, find no correlation between obstetricians/gynecologists density and cesarean delivery rates. However, such a study suffers from the possibility that omitted regional differences are correlated both with higher obstetricians/gynecologists density and cesarean utilization.[3]

Gruber and Owings (1996) test the demand induction model using an exogenous change in the financial environment facing obstetricians/gynecologists: declining fertility in the United States. Declining fertility acts as purely exogenous income reduction. They argue that the fall in fertility over the 1970-1982 period led obstetricians/gynecologists to substitute from normal childbirth towards a more highly

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[1] For criticisms of this approach see Phelps (1986).

[2] Rice (1984) provides the strongest evidence for induced-quantity increase in response to Medicare fee reduction in Colorado. A similar study by Hurley, Labelle and Rice (1990) for Ontario found mixed responses to fee changes across procedures. Evidence from the experience of the US and Canada offers a similarly mixed picture of the role of induced demand.

[3] This general criticism is supported by the evidence built by Dranove and Wehner (1994). Mimicking the Cromwell and Mitchell (1986) methodology, they found evidence that obstetricians density appears to induce births.

reimbursed alternative technology, c-section. Fertility fell by 13.5 percent during the period and cesarean utilization increased by over 240%. They find evidence of a strong correlation between within-state declines in fertility and within-state increase in c-section utilization, even if the general fertility decrease can explain only a small part of the overall growth in c-section utilization. These results suffer from the lack of control for changes in the structure of demand[4], technology, cost, reimbursement schemes and styles of practice.

Concerning c-section responses to fee and reimbursement changes Strafford (1990), examining c-section rates by payment source in a sample of California hospitals, finds that these are higher for the privately insured than for Medicaid patients - the first being more generously reimbursed than the second. However it seems that self selection problems strongly affect the consistency of estimated effects in this context. Keeler and Fok (1996) study the impact of an insurance reform under California Blue Cross that equalized fees for natural and cesarean delivery, a relative decline in cesarean fees of 21%. Using data from before and after the reform the authors find only a modest 0.7% reduction in c-section rates, which indicates a very small response to fee changes. As far as the average physician in their sample gets a large proportion of his income from the Health Plan that implemented the reform, income effect and the implied demand inducement should be very large. This seems to support the idea that when substitution effect is present it tends to confound the income (inducement) effects. Therefore, demand induction, even when income effect is extremely strong might be almost completely counterbalanced, and therefore obscured, by substitution effect[5].

The aim of this paper is to provide an enhanced empirical test of the demand induction model addressing the abovementioned limitations. We use an almost unique natural experiment on fees reduction which took place in an italian region, Emilia-Romagna, between 1997 and 1998. Fees for all delivery procedures where reduced by 20% by the regional financing authority in order to reduce

[4] For example, reduction in fertility might be accompanied by an increase in the degree of risk adversion among women in childbirth. Provided that the natural delivery is more risky, both for the mother and the child, we could observe an increase in c-section delivery even in absence of any induction.

[5] In a similar framework Gruber, Kim and Mayzlin (1999) provide empirical support to the obscuring effect of inducement behaviour due to substitution effects. They show that when income effects from fee changes are dominated by substitution effects, as it is with Medicaid insured, reimbursement increase of cesarean section can cause a real increase in the intensity with which Medicaid women in childbirth are treated.

regional outlays without inducing any change in hospital incentives for specific procedures. This fees reduction allows us to measure a pure income effect not affected by the counterbalancing impact of substitution effect.

We develop an extended version of demand induction model in the Newhouse (1970) and Evans (1974) tradition. A major limitation in these models is due to the homogeneity of patient types. Physicians do not account for any difference in patient riskiness, so that inducement is implicitly assumed not to differ across patients. This restriction imposes to evaluate the presence of demand induction on sample averages, and does not allow for a more comprehensive evaluation of demand induction on sample representative patient types. We remove this restriction by considering a discrete distribution of patients into classes of risk. In our context, a patient can choose between two main hospital types, public and private, which differ according to the way they are financed: public are fixed budgeted, private get reimbursed according to tariffs per Diagnosis Related Groups (DRG). We draw some new testable implications concerning the relative intensity of demand induction across risk classes. Briefly, these concern the comparison of inducement behaviour across different hospital types at a given point in time, the evaluation of the inducement behaviour resulting from an exogenous income shock, and the relative amount of inducement across risk classes.

In order to perform the corresponding empirical tests on inducement behaviour, we need first to set up a proper econometric model for the probability of c-section associated to the two types of hospitals, controlling for individual characteristics and risk factors. We follow Gruber and Owings (1996) and insert in a probit model explaining the c-section probability, a hospital type dummy. This is intended to capture some fixed, unobserved differences in style of practice, professionalism and technical endowments. However, as far as the utility patients attach to a given hospital type is correlated with the utility associated to a cesarean delivery, we cannot assume that hospital type dummies are exogenous for the parameters of the c-section probability model. In other words, a self-selection process is likely to occur, which would allocate the women in the two different types of hospital according to unobservable characteristics which could be among the determinants of the probability of c-section delivery. If exogeneity of the hospital type dummies is violated, consistent estimates of these probabilities can only be obtained only by joint modelling of the two latent variables governing c-section and hospital choice respectively.

Turning to the evaluation of the fee change, having available two repeated cross-sections, a convenient research tool is the “before and after design” with treated and untreated groups. This requires identifying a comparison group not affected by the policy intervention. According to our theoretical model, a proportional variation in fees - as we observe in our sample- does not lead to any change in inducement behaviour of fixed budgeted hospitals. Therefore, women deliverying their babies in public hospitals are excellent candidates to form the comparison group. Our analysis can then be casted in the framework of natural experiments in economics[6]. The major advantage of this approach is the possibility of evaluating the impact of the fee change on private hospitals controlling for concomitant changes which migth influence all deliveries across the two years. In the absence of endogeneity of the hospital type dummy, this could be achieved inserting in the c-section probit equation on the two pooled cross-sections a dummy variable for the second period. However, the sample selection mechanism outlined above, if present in both years, would assign women to the treatment group based on variables determining the probability of c-section delivery thus invalidating the resulting inference.

Following these considerations, we estimate on the two pooled cross-sections a simultaneous binary choice model, in which the second equation determines the hospital choice. This model represents the appropriate context in which the hypothesis of exogeneity of hospital type dummies for the c-section probability parameters can be tested. Since the exogeneity hypothesis can not be rejected, we are allowed to neglect the destination choice process and focus on the c-section probability equation in order to evaluate the empirical implications of our theoretical model. We evaluate the estimated model through the conditional moment approach suggested by Newey (1985), based on the so-called generalized residuals, and find no evidence against its specification. We therefore use the implied estimated probabilities to perform a statistical evaluation of the impact of the fee proportional variation for given class of riskiness and type of hospital.

We begin, in section 2, by providing some background on c-section delivery, the italian National Health Service and a brief description of the fees change we analyze in our paper. In section 3 we present a model that notes the implications of inducement-demand hypothesis for the use of c-section delivery when fees are reduced proportionally and patients differ in riskiness. Section 4 describes the data, the empirical specification and testing strategy adopted. Section 5 presents the main results and section 6 discusses them. Section 7 summarizes and concludes the paper.

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[6] For surveys on natural experiment methodology see Meyer (1995) and Rosenzweig and Wolpin (2000).

2 BACKGROUND ON C-SECTION DELIVERY AND OUR CASE STUDY

2.1 Cesarean section: some preliminary facts

C-section is increasingly adopted. According to OECD data [see **Figure 1]** we observe a steadily increase in c-section incidence across the sample, going from 6% in 1970 to more than 20% in 1998. This evidence is only partially consistent with WHO (1985) recommendations on appropriate technology for birth suggesting that "there is no justification, in any specific geographic region, to have more than 10-15% c-section births". Therefore this trend might be only partly interpreted as the consequence of the adoption of an appropriate technology for birth.

Once we look at some country specific data we do often observe an increase in c-section largely above the recommended standards. According to Gruber and Owings (1996), for instance, c-section in the USA increased to above 22% in the 1991. OECD data suggests that c-section adoption decreased afterwards[7]. Italy is clearly above this trend, reaching 25% in 1994. This evidence is confirmed and reinforced by our data. In our sample we find an incidence of about 26% across 1997-1998. A similar trend is to be found in Portugal and Mexico.

We have several potential explanations for this trend. One relies on a supply driven argument referring to the introduction and improvement in technologies for diagnosing fetal distress, such as electronic fetal monitoring [see Williams and Hawes (1979)]. Another potential cause of c-section adoption relates to the defensive behaviour of obstetricians due to the threat of a malpractice suit [see Dubay, Kaestner and Waidmann (1999)]. A third explanation refers to a demand driven trend: women in childbirth tend to increasingly ask for elective c-sections [for a debate on this topic see Paterson-Brown, Amu, Rajendaran and Bolaji (1998)].

Additional explanations can be found once we look at treatment choices as related to financial incentives. The cost for a c-section has been calculated in the UK at £668, including preoperative check (£6), the operation (£118), and a mean 4.2 days in the postnatal ward (£475), while the cost of inducing labour has been calculated at £644 for a nulliparous woman and £494 for a multiparous woman, including the induction, intrapartum care with delivery and a mean 2.1 days in the postnatal ward [see MacKenzie (1999)]. According to these figures, cost differential lies between 5 to 35%.

[7] Das (1997) illustrates the role HMO penetration can have in explaining this reverted trend for the US.

Reimbursement differentials tend to exceed cost differentials. Gruber and Owings (1996) suggest that c-section reimbursement premium is about 63% of natural delivery. In our case study c-section premium is more than 100% over natural delivery. Since c-section is more generously reimbursed than natural delivery, obstetricians facing income shocks might induce demand to increase their revenues. Within this context, Gruber and Owings (1996) suggest that declining fertility led to a substitution towards cesarean delivery in order to alleviate the income pressure on obstetricians.

Looking at the consequences of c-section adoption the evidence on its effectivness is mixed and partly inconclusive. Concerning the relationship between c-section and risk for the mothers, Lydon-Rochelle *et al*. (2000), conducting a population-based, retrospective cohort analysis, report that c-section delivery is associated with significantly higher risks of maternal rehospitalization among primipars without prior identified high-risk medical conditions. Looking at maternal mortality, Lydon-Rochelle *et al.* (2001), in a similar empirical framework conclude that c-section might be a marker for serious preexisting morbities associated with increased mortality risk rather than a risk factor for death in itself. Hall and Bewley (1999) exhamining direct deaths rates by mode of delivery in the UK show that the case fatality rate for all cesarean sections is six times that for vaginal delivery and even for elective c-section the rate is almost three times as great. Routine use of c-section for breech presentation is widespread. However, poor outcomes after breech birth might be the result of underlying conditions causing breech presentation rather than damage during delivery. Hannah *et al*. (2001), in a randomised trial comparing a policy of planned c-section with a policy of planned vaginal birth for selected breech-presentation pregnancies, show that there are no differences between groups in terms of maternal mortality or serious maternal morbidity. In the same study authors provide evidence of perinatal mortality, neonatal mortality and serious neonatal morbidity being significantly lower for the planned c-section group than for the planned vaginal birth group.[8] However, Ismail *et al*. (1999) and Danielian, Wang and Hall (1996), suggest that there is no firm evidence to recommend systematic elective c-section for breech presentation at term.

[8] In a Cochrane review Hofmeyr and Hannah (2000), having selected randomised trials comparing planned c-section for breech presentation with planned vaginal delivery, conclude that planned c-section greatly reduces both perinatal/neonatal mortality and neonatal morbidity, at the expense of somewhat increased maternal morbidity.

2.2 The italian NHS and delivery procedures[9]

The italian National Health Service (otherwise known as SSN-Servizio Sanitario Nazionale) was founded in 1978. It is a universal system that provides comprehensive health insurance coverage and uniform health care to the entire population. It is mainly financed through general taxation. However, depending on a citizens income, age and health condition, co-payments are also obligatory for drugs, ambulatory treatments, certain diagnostic and laboratory tests, and medical appliances.

The SSN is characterised by multiple different levels. At the central level, the Ministry of Health is responsible for national health planning, financing, general administration, and standards setting. Each year the Ministry allocates a fixed amount of resources according to a capitation rule to Regional Health Authorities (RHA). Public funds accruing to the 20 RHAs are then reallocated among approximately 200 Local Health Authorities (LHA) operating in whose territory. Within their given budget, LHAs are responsible for financing health care consumption of the assisted population, and are partly responsible for health service production.

The SSN guarantees the provision of hospital treatment at a given level of quality and free of charge. On the supply side, the SSN largely relies on public production supplemented by privately licensed hospitals. Public hospitals are run by LHAs or by autonomous public trusts (Aziende Ospedaliere). They are financed through fixed budget. Privately licensed hospitals can treat patients within the SSN, i.e. free of charge, and are afterwards refunded by the LHA to which the patient belongs. Private hospital refunding is based on the prospective payment of each clinical episode. Clinical episodes are classified according to Diagnosis Related Groups (DRG), a classification scheme that assigns each episode in one out of 492 codified groups. Each DRG is priced according to the amount of resource required for its treatment. Actually DRG is an "iso-resource" classification scheme. Public and private hospitals differ also according to quality and infrastructural capacity. Public hospitals are well endowed, while private tend to be less equipped. For our case study in delivery, relevant quality differences across hospital types are the following. With regard to hospital capacity we notice that public hospitals do have emergency surgical capacity and newborn intensive care units. Private do not have emergency room and therefore are not allowed to admit on an emergency. If we look at the style of practice, the presence of teaching personnel could reasonably increase the role of professional

[9] The description we provide here refers to the period covered in our case study. Major reforms took place thereafter changing the general framework of the National Health Service financing.

and deontic rewards in the public leading to a higher propensity to improve clinical practices and to adopt the more appropriate ones.

Patients are completely free to choose the treating hospital; it may be public or privately licensed, both within or outside their assisting LHA or region. Since patients are totally unaware of treatment costs, choice is essentially determined by distance from home, hospital specialization, waiting lists, and perceived quality.

2.3 A proportional reduction in fees for delivery procedures

The progressive reduction of funds accruing to health financing both at regional and local levels led the RHAs and the LHAs to reform and rationalize their expenditure and production patterns in order to gain efficiency and reduce costs. Within this framework, between 1997 and 1998 fees for all delivery procedures where reduced in Emilia-Romagna by 20%. **Table 1** provides the impact on total revenues for each type of hospitals in our case study. Revenues corresponds to outlays for the regional financing authority. In the Table we show expected reduction in regional outlays assuming that no substitution between natural and c-section delivery occurs in the meanwhile. Differences across type of hospitals are explained by small variations in market shares. If we compare these variation with the effective variation observed in the period we see that outlays reduced less than expected, in particular because of the relatively large reaction of private hospitals. Within this class of hospitals c-section revenues reduced by 6% instead of an extrapolated 28%, while natural deliveries contributed more than projected to the overall reduction in revenues. This aggregate evidence provide a background justification for our testing strategy of the demand-inducement hypothesis: we aim at testing if this compositional change in private hospitals in favour of cesarean delivery has been statistically significant.

3 A MODEL OF INDUCED DEMAND

In this section we outline a model of demand induction. It builds on the early work of Newhouse (1970) and Evans (1974), with extensions to fit our empirical framework.

We look at a representative hospital department admitting women in childbirth. We consider that women differ in risk. We assume that they are distributed into a discrete number of risk classes denoted by r, with $r=1, \ldots, R$. By convention we sort r so that $r>s$ implies that women in class r is riskier that women in class s. We posit that the hospital department has a utility function of the form:

$$
\begin{aligned}
&U = U(Y, I_1, ..., I_R) \\
&U'_Y > 0, U'_r < 0 \;\; \forall \; r = 1,...R \qquad (1) \\
&U''_{YY}, U''_{rr} < 0 \;\; \forall \; r = 1,...R
\end{aligned}
$$

where Y represents hospital department full income, earnings minus the value of foregone slack time, and I_r is the level of inducement on women of risk class r. For the sake of simplicity we assume here that the department is totally devoted to delivery procedures, i.e. is a specialized department. $U'_r<0$ arises by assuming that, as professionals bound by a code of ethics, physicians derive disutility from exploiting their agency relation to induce demand. We assume also that the deontic penalty is higher the lower is patient riskiness, i.e. $U'_s< U'_r$, with $r>s$.

Let p denote prospective payment for procedure and f fixed budget. The following model of induced demand studies p and f separately, identifying the relative magnitudes of their response to a change in the payment schedule. This change is exogenous and intervenes as a pure negative income shock. In this respect it resembles to the negative income effects due to a reduction in the stock of birth used in Gruber and Owings (1996) to identify demand induction. We begin with prospective payment for procedure.

3.1 Prospective payment for procedure

We follow McGuire and Pauly (1991) assuming additively separable preferences. Let:

$$U^p = U_Y(Y^p) + \sum_{r=1}^{R} U_r(I_r^p) \qquad (2)$$

$$Y^p = Y_N N^p + Y_c C^p \qquad (3)$$

where N is natural childbirths, C is cesarean, Y_N and Y_C are the full incomes from performing natural and c-section deliveries respectively, with Y_C - Y_N >0. That is we assume, following Gruber and Owings (1996), that the reimbursement premium for cesarean deliveries is sufficiently high to compensate the department for any loss in slack time from performing a c-section. This seems reasonable since cesarean fees are much higher, cesarean deliveries take less time and the increased difficulty of cesarean delivery does not compensate for the time reduction. We modify the revenue function to account for peculiarities in our case study as follows:

$$Y^p = Ty_N N^p + Ty_c C^p \qquad (3bis)$$

where y_N and y_C represent DRG weigth for natural and cesarean delivery procedures respectively and T is the payment due to each unit of DRG weigth.

Let B_r represents births by the women of risk class r. We define:

$$C^p = \sum_{r=1}^{R} f_r(i_r^p) B_r \qquad (4)$$

$$N^p = \sum_{r=1}^{R} \left(1 - f_r(i_r^p)\right) B_r \qquad (5)$$

$$I_r^p = i_r^p B_r \quad \forall\, r = 1, ..., R \qquad (6)$$

where i_r represents "inducement per birth" by risk class r. This is a costless effort that a physician exerts to induce demand for a c-section for a given birth of that class; $f_r(i_r)$ is the inducement function determining the c-section delivery rate, by risk class r, for each level of inducement effort. We assume that c-section delivery rate is increasing in inducement effort, i.e. $f'_r(x)>0$. We further assume that $f''_r(x)=0$. Since some fraction of births are appropriately diagnosed as requiring c-sections, we assume $f_r(0)>0$. Moreover, as far as c-section is more frequently appropriate for riskier women it follows that $f_r(0)> f_s(0)$, provided that $r>s$. See panel (a) of **Figure 2** for a graphical representation of c-section delivery rate functions in the case patients belong to two classes of risk, low and high.

The hospital maximizes (2) with respect to i_r, subject to (3bis) – (6). The first order conditions for an internal solution are (suppressing the superscripts):

$$U'_Y f'_r(i_r) T\Delta y + U'_r(i_r) = 0 \quad \forall\, r = 1,..., R \qquad (7)$$

where Δy represents $(y_C - y_N)$. See the panel (b) of **Figure 2** for a graphical representation of first order conditions for the high-low risk case. Therefore hospital physicians trade off the net disutility of inducement against the net utility from increasing income through shifting to cesarean delivery. In order to have an internal solution we have to assume that, for any risk class, r, the following hold:

$$U'_Y \, f'_r(0) T\Delta y > -U'_r(0)$$
$$U'_Y \, f'_r(i_{r,Max}) T\Delta y < -U'_r(i_{r,Max})$$

This means that at a zero level of induction there is a marginal increase in utility from inducement and that at the level i_{max}, i.e. once a marginal increase in induction does not increase the probability of c-section, the marginal deontic penalty is larger than the net utility from increasing income through shifting to cesarean delivery. Notice that, in equilibrium, for any couple of risk classes *h* and *l* such that *h*>*l*:

$$f'_l(i^*_l) - f'_h(i^*_h) = -\frac{U'_l(i^*_l) - U'_h(i^*_h)}{U'_Y \, T\Delta y} > 0 \qquad (8)$$

According to our assumption we are not able to establish any well behaved ordering in the equilibrium levels of induction effort across risk types.

Suppose now that the reimbursement per DRG weight, *T*, is exogenously reduced. Fully differentiating (7) we obtain:

$$\frac{\partial i_r}{\partial T} = -\frac{\left(U''_{YY}\,Y + U'_Y\right) f'_r(i_r)\Delta y}{\left[U''_{YY}\left(T f'_r(i_r)\Delta y\right)^2 + U''_{rr}(i_r)\right] B_r} \quad \forall\, r = 1, \ldots, R \qquad (9)$$

These expressions are strictly negative provided that $-U_{YY}/U_Y > 1/Y$, i.e., since 1/Y is approximately zero, as far as hospital physicians are at least slightly risk adverse. It seems quite resonable to assume that this condition holds both for public and private hospitals. In this case, therefore, equations (9) state that an exogenous, proportional decline in delivery procedures tariffs leads to more inducement in any class of risk. We are now in the position to say something about the relative intensity of these comparative statics effect across classes of risk. After some algebra and using equation (8) we see that:

$$\frac{\partial i_l}{\partial T} \gtrless \frac{\partial i_h}{\partial T} \quad \text{iff} \quad \frac{B_l}{B}\frac{\partial^2 U}{\partial i_l \partial i_l} \lessgtr \frac{B_h}{B}\frac{\partial^2 U}{\partial i_h \partial i_h} \quad \text{with} \quad l < h \qquad (10)$$

i.e. the increase of inducement effort is decreasing in the degree of patient riskiness provided that the reduction of marginal utility of inducement - weighted by class frequency -, is increasing in the degree of patient riskiness.

3.2 Fixed budget

Coming to the fixed budget model the revenue equation becomes:

$$Y^f = T\overline{y}(N^f + C^f) \tag{11}$$

where ` y is the capitated DRG weight for a delivery irrespective of the specific mode of delivery chosen. The first-order conditions obtained maximizing utility subject to the income and births constraint, as previously defined, show that in this case there is no income-related inducement effect. At the optimum the fixed budgeted hospital set the inducement effort to zero in order to minimize the deontic penalty. This implies that, for a given risk profile *r*, at the optimum $i_r^p > i_r^f$ and therefore, as far as we assume that induction function are the same for the fixed budgeted hospitals, $f(i_r^p) > f(i_r^f)$. In the fixed budget case it is trivial to observe that an exogenous, proportional decline in delivery capitated payment does not lead to any change in inducement.

3.3 Theoretical and empirical implications of our model: overview

In **Table 2** we outline the complete set of theoretical implications of our model and figure out the suitable testing strategies for each of them to be performed in the subsequent empirical analysis. Comparing to the existing literature we obtain a first set of implications (1) concerning the cross-section comparison of the marginal productivity of inducement efforts across risk types: the lower is patient riskiness the higher is the marginal "productivity" of inducement effort on c-section rates [see equation (8)]. This implication is not suitable for an empirical test, since we do not directly observe inducement efforts but only c-section rates, which realize according to a set of *R* unobservable inducement functions.

A second set of theoretical implications (2) concerns the cross-section probabilities of c-section across financing incentive schemes: assuming the constancy of induction functions across types of hospitals we expect c-section rates to be higher when hospitals are payed fee-for-service than when they are fixed budgeted. This is a well established result in the literature. In our model we generalize it to the complete set of patient risk classes. This implication is well suited for an empirical test since it implies a test on predicted probabilities.

Another well established set of theoretical implications concerns the inducement behaviour resulting from an exogenous income shock (3): negative income shocks lead to an increase in inducement effort when hospitals are payed fee-for-service, while they don't sort any effect if hospitals are fixed budgeted. In our model this has to be true irrespective of the patient risk type. We exploit this implication of the model considering women choosing public hospital as the control group of our experiment. The implication on private hospital is suitable for empirical test as far as we observe c-section rates differentials across the fee change and we maintain that the induction function is increasing in the induction effort.

A final set of implications, which is peculiar to our model, is related to the relative magnitude of the increase in inducement effort across risk classes. Consider a reduction in the marginal utility of inducement weighted by risk class frequency. If this reduction is increasing with patient riskiness, a negative income shock will produce an increase in inducement effort which is higher the less risky is the patient (4a). The reverse occurs if this reduction is decreasing with patient riskiness (4b). Maintaining that the marginal productivity of induction effort is decreasing in the patient riskiness we are able to partially test these implications. Two cases might occur. If we observe an increase in c-section rates which is larger the higher is patient riskiness we can infer that induction effort increased more on the more risky patient, thus leading to a rejection of 4a in favour of 4b. In the opposite case we cannot infer anything about the relative increase in induction effort and therefore on the curvature of hospitals' objective function.

4 EMPIRICAL MODEL

4.1 *The data*

We work on a sample of women in childbirth residing in Emilia-Romagna and admitted to regional hospitals for delivery. We excluded from our sample women going private, i.e. paying out-of-pocket for their hospital admission. Therefore patients are totally price insensitive. Patients going private are a negligible share of the overall hospital admissions in Italy. This sample refers to women not previously admitted for delivery within the same time interval. In order to exclude confounding factors due to the way hospital and health services are organized by LHA, we prefer to work on a sample of women residing and assisted by only one LHA, i.e. the one of the regional major city, Bologna. This LHA assists a population of about 900 thousands inhabitants, representing almost 25% of the regional overall population. **Table 3** provides some descriptive evidence on the distribution of c-section delivery across the two years in our sample.

4.2 *The simultaneous binary response model*

In order to set up a testing framework for the implications of our theoretical model, we first need to specify an econometric model to explain the individual probability of c-section delivery. This model must be able to predict the differential adoption of c-section delivery across different types of hospitals, controlling for covariates determining individual riskiness. Different hospitals tend to treat differently the same patient. This can be due to several factors as financial incentives, professional rewards, emergency surgical capacity availability.[10] Therefore, hospital type effects must be allowed in the specification of the c-section probability, in the form of both additive and multiplicative hospital type dummies to measure the differential effects produced by the same individual risk factors across different hospital types.

However, it can be argued that the hospital type dummies are endogenously determined, as far as the probability of c-section depends on unobservable variables which are correlated with unobserved characteristics affecting the hospital choice. This would make estimation of c-section probability unconsistent. Suppose that private providers are more inclined to treat with the higher intensity. As far as patients are aware of this, women with unobservable high propensity for c-section are more likely to select the private hospital. This would lead us to overestimate the private c-section probability. Similarly, we are likely to underestimate this probability for the public if this is the chosen destination of women with higher propensity to a natural delivery.

To provide for the above features, we formulate the following simultaneous binary response model[11] for the individual probability of c-section delivery and the choice between private and public hospital of woman *i, i=1…N*:

$$c_i^* = a_1 + b_1' \underline{z}_{1i} + g_1 h_i + d_1' h_i \underline{z}_{1i} + u_i = J_1' \underline{x}_{1i} + J_2' h_i \underline{x}_{1i} + u_i \qquad (12)$$

$$h_i^* = \boldsymbol{a}_2 + \boldsymbol{b}_2' \underline{z}_{2i} + v_i = \boldsymbol{J}_3' \underline{x}_{2i} + v_i \qquad (13)$$

with:

$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim NIID\left(\underline{0}, \begin{bmatrix} 1 & \boldsymbol{r}_{12} \\ \boldsymbol{r}_{12} & 1 \end{bmatrix} \right)$$

[10] See also WHO (1985) recommendations suggesting that "natural deliveries after a Cesarean should normally be encouraged wherever emergency surgical capacity is available".

[11] Endogenous dummy models have been firstly indroduced by Heckman (1978). The most relevant cases in qualitative choice models have then been systematically presented in Maddala's book (1983).

$$\underline{x}_{1i} = (1 \quad \underline{z}_{1i}^{'})^{'}, \qquad J_1^{'} = (a_1 \quad b_1^{'}), \qquad J_2^{'} = (g_1 \quad d_1^{'}),$$

$$\underline{x}_{2i} = (1 \quad \underline{z}_{2i}^{'})^{'}, \qquad J_3^{'} = (a_2 \quad b_2^{'}),$$

where both outcomes are observed as binary response variables:

$$c_i = \begin{cases} 1 & if \quad c_i^* > 0 \\ 0 & otherwise \end{cases} \qquad\qquad h_i = \begin{cases} 1 & if \quad h_i^* > 0 \\ 0 & otherwise \end{cases}$$

with $c=1$ in case of c-section delivery, $h=1$ if private hospital is the chosen destination; $\underline{z}_{1i}$ is a vector of individual risk factors, including previous c-section delivery suffered by the woman, breech presentation of the baby, age and recent hospital admission; $\underline{z}_{2i}$ is a vector of variables which determine the hospital choice, including, beside some risk factors, the distance from the hospital, and some characteristics of the town in which the woman resides (see **Table 4**). Identification of the model requires that $\underline{z}_{2i}$ does not include all the variables contained in $\underline{z}_{1i}$.

Exogeneity of h in the equation for $c*$ is violated as far $\boldsymbol{r}_{12} \neq 0$, making estimates of the parameters of equation (12) unconsistent. On the contrary, if h is found to be exogenously determined, the joint model can be reduced to the c-section probability equation, which is conditional to the hospital choice, while equation (13) can be left out from the analysis. Our model in (12) and (13) generalizes Maddala's model 6 (chapter 5) for simultaneous equations with two binary responses. That model, which has been recently applied by Holly *et al.* (1998)[12], only considers the additive effect of the one observed variable on the latent indicator of the other. In order to test the exogeneity of the dummy variable ($H_0 : \boldsymbol{r}_{12} = 0$), we extend Maddala's model by inserting in the first equation the interaction term involving the endogenous dummy variable and the explanatory variables $\underline{z}_{1i}$. This is an important generalization whenever it can not be assumed *a priori* that the first equation explanatory variables do not have a differentiated impact on the latent dependent variable according to the potentially endogenous dummy variable indicator. Actually, if $\boldsymbol{d}_1^{'} \neq 0$, but the interaction term is omitted, the additive dummy term in equation (12) becomes correlated with the resulting error component. This will affect the outcome of the exogeneity test and could result in a wrong evaluation of the dummy exogeneity status.

[12] The objective of their analysis is the joint modelling of health care utilization and health insurance in Switzerland.

4.3 Evaluating the impact of the fee changes across the two years

We look at the change in fees as the possible source of a structural break in the parameters of model (12-13). Having available two independent repeated cross-sections in years 1997 and 1998, a test of parameter constancy can be performed after their pooling, introducing in both equations a dummy variable taking value 1 for women delivering their baby in year 1998 (*d98*). The fee change is expected to affect only the parameters of the process determining c-section probability conditional on the chosen hospital. Nevertheless, we need to control for the constancy of the parameters of the marginal destination process in order to exclude the possibility that variations in the parameters of the conditional model are brought in by an eventual structural break investing the marginal model parameters. We keep the model as general as possible and allow both intercept and slope variations in the regression parts of the latent model, rewriting equations (12) and (13) as:

$$c_i^* = J_1^{'} \underline{x}_{1i} + J_2^{'} h_i \underline{x}_{1i} + f_1^{'} d\,98\, \underline{x}_{1i} + f_2^{'} d\,98\, h_i \underline{x}_{1i} + u_i \tag{14}$$

$$h_i^* = J_3^{'} \underline{x}_{2i} + f_3^{'} d98 \underline{x}_{2i} + v_i \tag{15}$$

i=1,…N.

The first equation of the above model is a latent dependent variable analogue of the linear regression model which is commonly used for the evaluation of policy changes with two cross-sections pooled across time.[13] Our model extends this empirical literature by accounting for endogenous selection of the control group, which represents one of the major threats to the validity of the interpretation of the results (see Meyer, 1995, paragraph 2, point 7).

The constancy of the whole set of parameters of the hospital choice model can be evaluated, after estimation of the above simultaneous model, as a test of the hypothesis:

$$H_0^{dest} : f_3 = 0,$$

while the presence of a structural break on one or both parameter sets of the conditional c-section probability model amounts to rejection of the corresponding following null hypotheses:

[13] This leads to the so called "difference in differences technique".

$H_0^{ces,\,pub} : f_1 = 0$
$H_0^{ces,\,priv} : f_2 = 0$

The first hypothesis is related to possible changes due to technical progress or variation in tastes investing all delivery procedures across the two years. These are measured on the control group. On the other hand, the impact of the fee change can be evaluated via the second hypothesis, corresponding to the treated group of women deliverying in private structures. Notice that evidence in favour of H_0^{dest} supports the constancy of the endogenous selection mechanism allocating women in the two kind of hospitals.[14]

5 *ESTIMATION RESULTS*

5.1 Simultaneous probit estimation and exogeneity test

Given the great simplification implied by the exogeneity condition, we start our specification analysis by estimating the simultaneous model (14 and 15). We use all the available information on risk factors, inserting all their interactions with fee change and private hospital dummies and with both dummies, as far as they exhibit sufficiently high non-zero frequency and variability across the delivery outcome. **Table 5** shows estimated coefficients[15] and associated heteroskedastic consistent standard errors of two specifications. In the left-hand side we present the more general one, corresponding to

[14] Ideally, separate estimation on the two years would allow for unconstrained estimate also of the correlation coefficient of the two stochastic components. We experimented with this possibility, founding evidence of weak identification of the model. However, it is plausible to assume that the way women select themselves in a particular kind of hospital remains unchanged in two subsequent years, as far as they have no information on the ongoing financial reform.

[15] Estimation has been performed via numerical maximization using Gauss 3.0 and programming appropriate code for the likelihood function corresponding to the simultaneous two equation probit and a for the corresponding analytical first order derivatives (see appendix 2). Analytical computation of the first order-derivatives reduced considerably the computational time needed by the maximization routine and made it possible to resort to the Newton algorithm, with numerical evaluation of second order derivatives based on the provided first-order ones. The algorithm converged in 3 iteration, with an average time for iteration about equal to 3 minutes on a 1000 Mherz processor computer machine. All the elements of the gradient vector at maximum are 0 up to the 11-th decimal point.

equations (14) and (15), which we use to test a number of restrictions. Firstly, having observed that the coefficients of the age dummies are similar in their absolute value and of contrary sign, we test the corresponding linear restrictions and find them statistically valid. As a consequence, we replace the two age dummies with the variable *Agedum=age36-age25*[16] in the c-section equation. Secondly, the likelihood-ratio test statistic for the hypothesis H_0^{dest} is equal to 12.792, which compared with a critical value of 22.36 (95% critical value of the Chi-square distribution with 13 d.f.) provides strong evidence in favour of the constant representation of the hospital choice model. In the specification presented in the right-hand side of the table we impose the abovementioned tested constraints. Notice that the coefficient of the variable *Distance 2* becomes significant, indicating this variable as a relevant component of opportunity cost in patient hospital choice. Finally the estimated correlation coefficient turns out to be not significantly different from zero, and the exogeneity hypothesis $H_0 : r_{12} = 0$ can not be rejected. As a consequence of this result, we reduce our model to equation (14) and focus on the evaluation of the impact of risk factors, hospital type and fee change on the probability of c-section delivery.

5.2 Estimation results for the c-section equation

In this second stage of the analysis we focus on the c-section process, and estimate equation (14) by a simple probit model.[17] This is a particularly convenient compact representation for testing the empirical implications of our theoretical model. The final specification of the model is presented in **Table 6.** We first test the hypothesis $H_0^{ces,pub}$ and can not reject the corresponding exclusion restrictions. This result is encouraging, as it reveals that no systematic intertemporal changes occured between the two years in the process determining delivery technology. We expected this finding given the very short run nature of the policy change we analyse. As a consequence, we exclude from the model the block of variables represented by the interactions of risk factors and year 98 dummy. On the contrary, we reject $H_0^{ces,priv}$ and can not eliminate the analogous block of interactions of the fee change with private hospital type dummy, mainly do the highly significant coefficient of the private

[16] This variable results equal to -1 for women aged less than 25, 0 for women between 25 and 36 and 1 for women more than 36 years old.

[17] We use the numerical maximization routines automatically implemented by STATA 6.0 for single equation probit estimation.

hospital type dummy interacted with the fee change indicator. This structural break on the c-section probability model parameters evidences the significant impact of the financial shock due to the fee change in hospitals payed fee-for-service. Also, notice the positive and significant coefficients of the considered risk factors on c-section probability, in agreement with the existing results in the literature. We leave more extended comments to the next section, where we illustrate our results in terms of predicted probabilities. Together with the estimation results we provide, in **Table 6**, some misspecification tests aimed at examining whether the main assumptions of the model are supported by the data. We follow the proposal of Newey (1985), reviewed and extended by Pagan and Vella (1989), and resort to the formulation of different conditional moment restrictions which have to hold if the model is adequate. Let us rewrite, with obvious compact notation, model (14) as:

$$c_i^* = \beta' \underline{w}_i + u_i ;$$

the sample moment condition used to build up diagnostic tests in probit models is characterized as:

$$\tau = \frac{1}{N}\sum_i z_i \hat{u}_i = \sum_i m_i = 0$$

where:

$$\hat{u}_i = \hat{\phi}_i (y_i - \hat{\Phi}_i)\hat{\Phi}_i^{-1}(1-\hat{\Phi}_i)^{-1}$$

is the generalized residual[18] (see Chesher and Irish, 1987 and Gourieroux et al., 1987), $\phi(.)$ denotes the standard normal density function, and hat and subscript i indicate evaluation at $\hat{\beta}' \underline{w}_i$. Pagan and Vella show that different choices of z_i lead to the following misspecification tests:

- *Omitted variables (x):* $z_i = x_i$
- *Heteroscedasticity* $(\sigma_i^2 = \exp(\gamma x_i))$*:* $z_i = x_i (\hat{\beta}' \underline{w}_i)$
- *Normality:* $z_i = (\hat{\beta}' \underline{w}_i)^2 ; z_i = (\hat{\beta}' \underline{w}_i)^3$

and that it is possible to test if statistic that the conditional moments are actually zero, by regressing m_i against unity and the scores of observation i and testing if the coefficient of the intercept is zero. The

[18] The generalised residual is an estimate of the expected value $E(u_i | y_i)$, i.e. the best prediction of the error term, which would depend on the unobservable dependent variable.

results contained in **Table 6** generally support the good specification of the estimated model, and the validity of the inference we want to perform on the implied estimated probabilities.

5.3 *Testing the implications of the theoretical model on predicted probabilities*

In this section, we focus on predicted probabilities, which are more easily interpretable than the coefficients themselves, in order to get a more direct feeling of the relative role of the various explanatory variables in determining the outcome of interest. Our objective is the comparison of the probability of c-section delivery for reference individuals exhibiting particular values of the exogenous variables.

Let us stack in one vector the probability of delivering via c-section of two reference women with vector of characteristics $\underline{w}_1^{'}$ and $\underline{w}_2^{'}$ respectively:

$$p(\boldsymbol{b}) = \begin{bmatrix} p_1(\boldsymbol{b}) \\ p_2(\boldsymbol{b}) \end{bmatrix} = \begin{bmatrix} \Phi(\underline{w}_1^{'}\boldsymbol{b}) \\ \Phi(\underline{w}_2^{'}\boldsymbol{b}) \end{bmatrix}$$

The above quantities can be estimated by using the MLE $\hat{\boldsymbol{b}}$. We show in Appendix 3 that asymptotic normality of $\hat{\boldsymbol{b}}$ implies asymptotic normality of the estimated probability vector $\hat{p} = p(\hat{\boldsymbol{b}})$ by virtue of the Theorem of the Differentiable Transformation. In particular, $\hat{p}$ is asymptotically distributed as a bivariate normal with matrix of variance and covariance $V = \{v_{ij}\}$, whose expression is given in the appendix. The joint distribution of the two estimated probabilities is needed in order to evaluate a test statistic for the hypothesis $H_o : p_1 - p_2 = 0$, which aims at enlighting wheather the variations induced in the probability of c-section by variations in the vector of characteristics $\underline{w}$ are significantly different from zero. A test statistic for the above hypothesis is simply given by $S = (\hat{p}_1 - \hat{p}_2) \big/ \sqrt{\hat{v}_{11} + \hat{v}_{22} - 2\hat{v}_{12}}$, which is asymptotically distributed as a standard normal.

In the following tables we use this statistical tool to test the various predictions on c-section probability implied by our theoretical model for different risk levels presented by the woman in childbirth. We evaluate the estimated probabilities for both years at four different individual risk classes [for a definition of each class see the footnotes at **Tables 7a, b** and **c]**.

Starting with implication 2 [**Table 7a**], we see that for any given risk class the c-section probability is systematically and significantly higher in private hospitals - financed through tariffs - than in public ones - which are fixed budgeted - after the proportional fees change; on the contrary we don't observe any significant discrepancies before the financing reform. These results are consistent with implication 2 of our theoretical model.

The main focus of our analysis is to compare c-section probabilities across the fees change [see **Table 7b**]. In particular, as far as private hospitals are risk adverse, a proportional reduction in tariffs for delivery procedures, will result in an increased induction effort. As expected, we observe large and significant increases in the c-section probability at any level of individual risk for patients admitted to private hospitals. This result is consistent with implication 3 of our theoretical model.

Coming to implication 4 [see **Table 7c**] our results suggest that the marginal increase in c-section probability due to proportional fees reduction is significantly less marked on the more risky type (class 4) compared to the less risky one (class 1 and 2). All the other comparisons turn out to be not statistically significant. Thus, concerning the relative increase in inducement effort across risk classes, this evidence is inconclusive, i.e. demand induction could be either more, less or equally pronounced the more risky is the patient.

6 DISCUSSION

Our analysis provide two sets of results: one about the relationship between patient hospital choice and demand induction and one about the induction behaviour of risk adverse health service providers.

We work on a case study where patients can freely choose among a set of hospitals. Hospitals differ in terms of quality, capacity, style of practice and financing schemes. These aspects indicate the propensity to choose a type of hospital as a relevant factor for treatment choice. In our empirical analysis we couldn't assume away that patients might self select into hospitals types according, at least partially, to treatment behaviour of the providers. In order to account for this we adopt a general econometric specification where the latent equation determining c-section probability is simultaneously modelled with the hospital choice latent regression. We then test the hypothesis of exogeneity of the hospital type dummies for the parameters of the c-section probability and can not reject it. This result, which leads to a noticeable simplification of the model, is interesting in itself since it suggests that patients choice of the provider is determined exogenously from hospital treatment and inducement behaviour. Apparently, hospital choice and treatment choice are not affected by any common set of unobservable variables. With rational and fully informed patients and given patient preferences on treatment behaviour, we would expect that exogeneity cannot be accepted. The same would happen if treatment and hospital choice were affected by common unobservable individual risk factors. According to our evidence we have to exclude both. To our knowledge this finding is totally new in the health economics literature and deserves a more careful investigation than that we conducted here.

Coming to demand induction we provide robust evidence of the presence and magnitude of this behaviour. According to our estimates, in response to a 20% income shock, c-section adoption increase of 65% for a low risk woman (type 1) being representative of more than 50% of our sample. The exact increase of inducement effort cannot be figured out without making assumptions on its marginal productivity. Anyway, even considering inducement effort extremely productive, we might conclude that inducement increase is pretty high in the low risk patient. Once we look at a high risk woman (type 4), representing not more than 3% of the sample, we measure a significantly smaller increase in c-section probability of about 4%. This evidence does not allow to say anything conclusive about the relative increase in inducement effort across these two classes of risk. However, according to our figures, we can observe that the marginal productivity of inducement effort has to be more that 16 times larger in the low risk class than in the high risk one in order to interpret this differential increase in c-section probability as due to an increase in induction effort that is larger on the higher risk type. Therefore, provided that the marginal productivity of inducement effort is not so different across types, it seems that in our sample the income shock produce an increase in inducement that is larger on the low risk type.

This euristic result have a quite relevant policy implication. The usual policy to control for demand induction is tariff discrimination, which typically amounts to reducing reimbursement premiums on the low risk patients. As a first alternative policy measure, consider increasing patient awarness of inducement behaviour through health education campaigns. This might reduce the marginal productivity of inducement leading, *coeteris paribus*, to a reduction in the equilibrium level of inducement effort for that class of patients. A similar effect might occur by investing on the deontic penalty physicians might suffer because of an excess of induction. Our analysis suggests that both policy interventions have to be mainly targeted to the low risk patients.

7 CONCLUSIONS

The "induced-demand" model, as that of McGuire and Pauly (1991), states that in the face of negative income shocks, physicians may exploit their agency relationship with patients by providing excessive care. This misbehaviour, called demand induction, is endemic to the health economy and represents one of the more disruptive circumstances for the competitive allocation of resources in this sector. Despite its paramount relevance there is very little robust evidence in the literature on its extent. We address this limitation and propose an extended version of the “induced-demand” model that allows for patient heterogeneity, considering a discrete distribution of patients into classes of risk. Within this framework we are able to draw new testable implications concerning the relative intensity of demand induction across risk classes and to test them on sample representative patient types. Our model is of general interest since it applies whenever a supplier is able to orientate consumers, according to financial incentive, over a set of partially substitutable "treatments".

We test the model on a sample of delivery choices. Cesarean section and natural delivery are the alternative technologies for birth the provider might choose. Income shock on the providers is produced by a natural experiment on fees change. A proportional fee reduction on the two treatments is observed in our sample. This allows us to evaluate a pure demand induction effect not obscured by any substitution effect due to the change in relative fees typically examined in the literature.

Our empirical specification adopt a two equations simultaneous probit model in which the hospital choice is endogenous to the treatment choice equation. This model is of general interest in the health econometrics literature and could be extensively adopted in similar context of analysis to investigate the largely ignored relationship between hospital choice and propensity to adopt a given treatment technology. Acceptance of the exogeneity condition leads to a noticeable simplification of the model, making the c-section delivery probit formulation conditional on the kind of hospital chosen a valid tool for the inference about the impact of the fee change. This can be interpreted as a structural break on the parameters of the conditional model, whose constancy across the reform can be statistically evaluated. Thanks to the implications of our theoretical model, public hospital deliveries can be chosen as the control group, since they are not affected by the particular policy change we analyse.

Our evidence suggests that risk adverse providers overused cesarean delivery for all profiles of individual risk considered, relative to the level that would be chosen by a financially disinterested provider. The magnitude of the effect has never been so clearly spotted in the literature before. We don't find any clear evidence of demand induction being more marked the less risky is the patient. However, this is a reasonable implication provided that the marginal productivity of inducement effort is not disproportionately higher in the low risk type comparing to the high risk one.

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8 APPENDIX 1

Table A1: Descriptive statistics for the c-section equation variables.

	Full sample	**Natural delivery**	**C-section delivery**
	N° obs. = 10343	N° obs. = 7643	N° obs. = 2700
Private	4.7%	4.6%	4.9%
Fee change	50.0%	49.8%	50.3%
Age25	8.8%	9.8%	5.8%
Age36	17.5%	15.3%	23.5%
Previous	20.2%	18.5%	25.2%
Prior	7.0%	1.0%	24.3%
Breech	4.8%	0.3%	17.6%

Table A2: Descriptive statistics for the c-section equation variables.

	Public hospitals		**Private hospitals**	
	1997	**1998**	**1997**	**1998**
Variable	N° obs. = 4921	N° obs. = 4938	N° obs. = 255	N° obs. = 229
Age25	8.9%	8.8%	7.8%	6.1%
Age36	17.8%	17.2%	17.3%	16.2%
Prior	6.9%	7.3%	7.1%	5.7%
Breech	4.6%	5.1%	5.1%	4.8%
Previous	20.6%	20.8%	10.6%	10.0%
C-section	26.1%	26.1%	23.9%	30.6%

Table A3: Descriptive statistics for the hospital choice equation variables.

	Women NOT residing in BOLOGNA				Women residing in BOLOGNA			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
	N° obs. = 6985				N° obs. = 3358			
Age	31.12	4.58	15.23	46.32	32.40	4.93	16.64	47.23
Car	0.03	0.01	0.02	0.04	0.04	0.0	0.04	0.04
Distance 1	16.1	11.6	0.0	63.0	0.0	0.0	0.0	0.0
Distance 2	28.5	15.9	6.0	78.0	0.0	0.0	0.0	0.0
Travelled Dist.	23.2	17.0	0.0	132.0	2.07	10.6	0.0	117.0
Population	19.1	18.6	1.2	64.0	384.5	0.7	383.8	385.1
Elderly	1.60	0.38	0.87	3.1	2.801	0.000	2.801	2.801
Mean Income	24898	2768	17707	31515	31032	173	30854	31200

9 APPENDIX 2

For ease of exposition, we report the log-likelihood of the simultaneous model in 12 and 13. The log-likelihood of model corresponding to 14 and 15 has the same form, but includes among the explanatory variables also the dummies corresponding to the fee change.

$$L(J_1, J_2, J_3, r_{12}) = \sum_{i=1}^{N} \left[c_i h_i \ln P_i^{11} + c_i (1-h_i) \ln P_i^{10} + (1-c_i) h_i \ln P_i^{01} + (1-c_i)(1-h_i) \ln P_i^{00} \right]$$

where:

$$P_i^{11} = F(J_1^{'} \underline{x}_{1i} + J_2^{'} \underline{x}_{1i}, J_3^{'} \underline{x}_{2i}; r_{12})$$
$$P_i^{10} = F(J_1^{'} \underline{x}_{1i}, -J_3^{'} \underline{x}_{2i}; -r_{12})$$
$$P_i^{01} = F(-J_1^{'} \underline{x}_{1i} - J_2^{'} \underline{x}_{1i}, J_3^{'} \underline{x}_{2i}; -r_{12})$$
$$P_i^{00} = F(-J_1^{'} \underline{x}_{1i}, -J_3^{'} \underline{x}_{2i}; r_{12})$$

and $F(.,.; r_{12})$ is the joint normal distribution function of the model error terms (u_i, v_i).

The first order derivatives of the above log-likelihood function with respect to the parameters can then be evaluated by resorting to the following formula, which provides first order derivatives of the bivariate normal density function generally expressed as $F\left[a_1(g_1), a_2(g_2); r\right]$:

$$\frac{\partial F}{\partial g_1} = \frac{1}{F} \Phi\left(\frac{a_2 - r a_1}{\sqrt{1 - r^2}}\right) j(a_1) \frac{\partial a_1}{\partial g_1}$$

$$\frac{\partial F}{\partial g_2} = \frac{1}{F} \Phi\left(\frac{a_1 - r a_2}{\sqrt{1 - r^2}}\right) j(a_2) \frac{\partial a_2}{\partial g_2}$$

$$\frac{\partial F}{\partial r} = \frac{1}{F} \exp\left\{ -\frac{(a_1^2 + a_2^2 - 2 r a_1 a_2)}{2(1 - r^2)} \right\} \frac{1}{(2p\sqrt{1 - r^2})}$$

10 APPENDIX 3

Asymptotic normality of maximum likelihod estimator, $\hat{b}$ is a standard result. In our probit model, the parameter vector dimension is equal to *K* and we have:

$$\sqrt{N}(\hat{\boldsymbol{b}} - \boldsymbol{b}_0) \xrightarrow{d} N_K(\underline{0}, \Sigma)$$

where $\boldsymbol{b}_0$ is the value of the parameter which maximize the limit likelihood function.

We can obtain the asymptotic distribution of the estimated probabilities by recognizing them as a differentiable function of the MLE $\hat{\boldsymbol{b}}$. More precisely, we want to write down the joint asymptotic distribution of two particular such probabilities, corresponding to different reference individuals.

With the notation of section 4.5, let us regard $p(\boldsymbol{b})$ as a function $p : R^K \to [0,1]^2$:

$$\underset{2\times 1}{p(\boldsymbol{b})} = \begin{bmatrix} \Phi(\underline{w}_1^{'}\boldsymbol{b}) \\ \Phi(\underline{w}_2^{'}\boldsymbol{b}) \end{bmatrix}.$$

Noticing that $p(\boldsymbol{b})$ is differentiable in $\boldsymbol{b}_0$, with:

$$\underset{2\times K}{p'(\boldsymbol{b}_0)} = \left.\frac{\partial p(\boldsymbol{b})}{\partial \boldsymbol{b}^{'}}\right|_{b=b_0} = \begin{bmatrix} f(\underline{w}_1^{'}\boldsymbol{b}_0)\underline{w}_1^{'} \\ f(\underline{w}_2^{'}\boldsymbol{b}_0)\underline{w}_2^{'} \end{bmatrix}$$

and that the rank of $p^{'}(\boldsymbol{b}_0)$ is equal to 2, we can apply the Theorem of the differentiable transformation and get the result:

$$\sqrt{N}\left[p(\hat{\boldsymbol{b}}) - p(\boldsymbol{b}_0)\right] \xrightarrow{d} N_2(\underline{0}, V)$$

with:

$$\underset{2\times 2}{V} = \left.\frac{\partial p(\boldsymbol{b})}{\partial \boldsymbol{b}^{'}}\Sigma\frac{\partial p(\boldsymbol{b})}{\partial \boldsymbol{b}}\right|_{b=b_0}$$

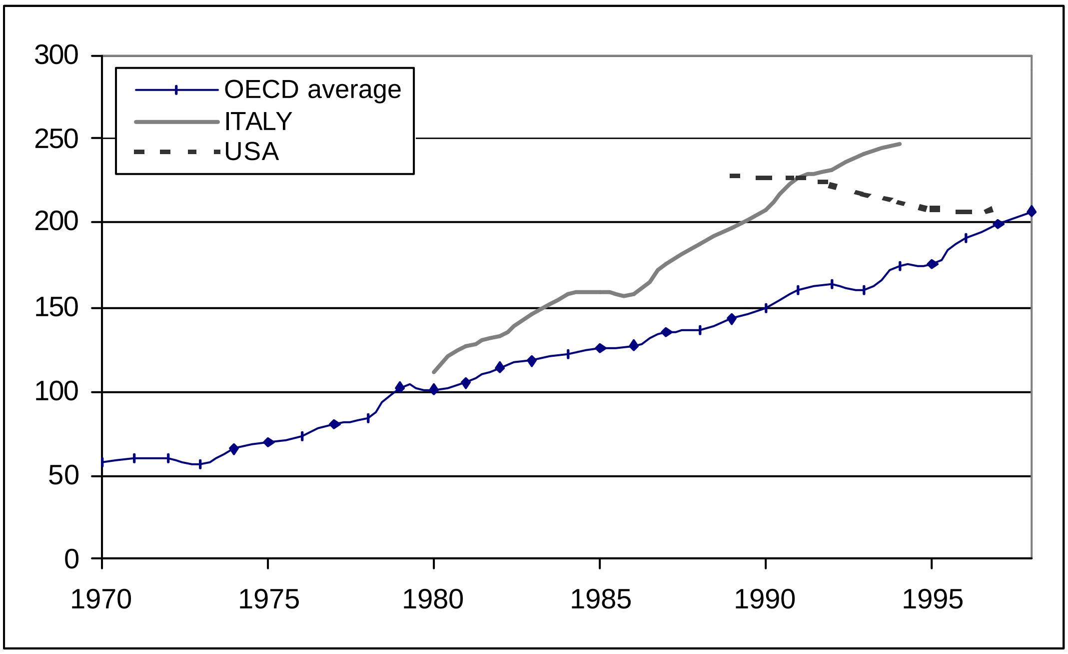
The finite sample counterparts of the elements of V can then be consistently estimated by:

$$\hat{v}_{11} = \frac{1}{N} f(\underline{w}_1^{'}\hat{\boldsymbol{b}})^2 \underline{w}_1^{'}\hat{\Sigma}\underline{w}_1 \; ; \; \hat{v}_{22} = \frac{1}{N} f(\underline{w}_2^{'}\hat{\boldsymbol{b}})^2 \underline{w}_2^{'}\hat{\Sigma}\underline{w}_2 \; ; \; \hat{v}_{12} = \frac{1}{N} f(\underline{w}_1^{'}\hat{\boldsymbol{b}}) f(\underline{w}_2^{'}\hat{\boldsymbol{b}})\underline{w}_1^{'}\hat{\Sigma}\underline{w}_2$$

where $\hat{\Sigma}$ is a consistent estimate of Σ.

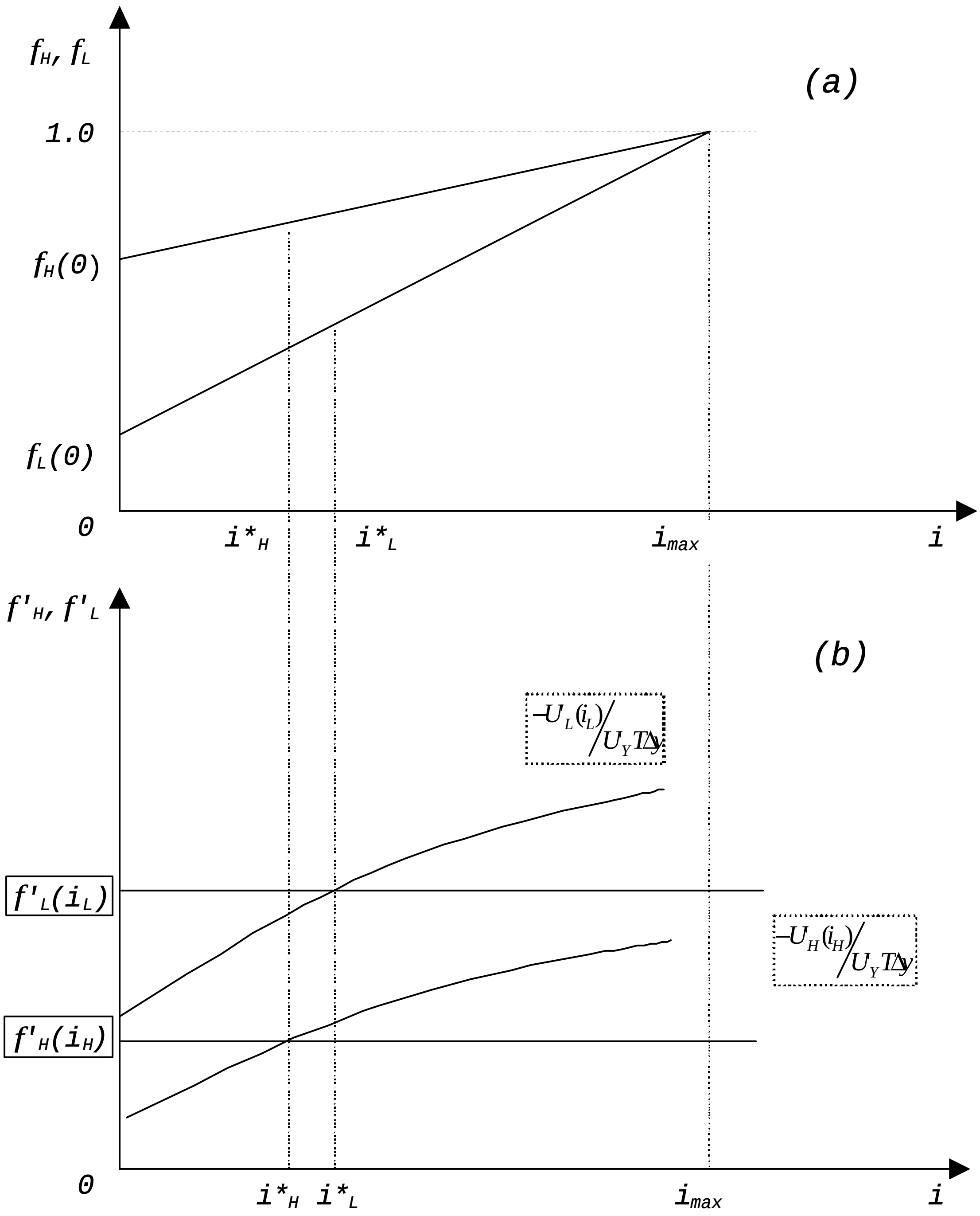
FIGURES

Figure 1: The incidence of C-section in OECD coutries. Cesarean-sections per 1000 live birth.



Source: Our elaborations on OECD Health Data, 2000. The OECD average is calculated as a simple mean of the following countries rates: Belgium, Czech Rep., Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Luxembourg, Mexico, Norway, Portugal, Spain, Sweden, Switzerland, U.K.,USA.

Figure 2: Graphical rapresentation of equilibria with two classes of risk: L (low) and H (high).



TABLES

Table 1: Variation of revenues from delivery procedures. 1998-1997. Values expressed in Euro.

		1997	1998	Effective % variation	Extrapolated % variation
Public hospitals	C-section deliveries	1,981,690	1,609,742	-18.8%	
	Natural deliveries	2,862,316	2,287,956	-20.1%	
	All deliveries	4,844,006	3,897,698	-19.5%	-19.7%
Private hospitals	C-section deliveries	86,944	81,344	-6.4%	
	Natural deliveries	140,795	92,315	-34.4%	
	All deliveries	227,738	173,659	-23.7%	-27.9%

Table 2: Theoretical and empirical implication of our demand-induction model.

Theoretical implications	Empirical test
1. $f'(i_R) < ... < f'(i_r) < ... < f'(i_1)$	No test
2. $i_r^p > i_r^f \Rightarrow f(i_r^p) > f(i_r^f)\ \forall r \in R$	Test: $f(i_r^p) > f(i_r^f)$
3. under prospective tariffs: $\frac{\partial i_r^p}{\partial T} < 0\ \forall r \in R$	Mantaining $f'(i_r^p) > 0$, test: $\frac{\partial f(i_r^p)}{\partial T} = f'_r \frac{\partial i_r^p}{\partial T} < 0 \Leftrightarrow \frac{\partial i_r^p}{\partial T} < 0$
4a. $\frac{\partial i_l}{\partial T} < \frac{\partial i_h}{\partial T}$ iff $\frac{B_l}{B}\frac{\partial^2 U}{\partial i_l \partial i_l} > \frac{B_h}{B}\frac{\partial^2 U}{\partial i_h \partial i_h}$ with $l < h$ 4b. $\frac{\partial i_l}{\partial T} > \frac{\partial i_h}{\partial T}$ iff $\frac{B_l}{B}\frac{\partial^2 U}{\partial i_l \partial i_l} < \frac{B_h}{B}\frac{\partial^2 U}{\partial i_h \partial i_h}$ with $l < h$	Mantaining $f'(i_h^p) < f'(i_l^p)$ if $\frac{\partial f(i_l)}{\partial T} \leq \frac{\partial f(i_h)}{\partial T} \Rightarrow \frac{\partial i_l}{\partial T} \gtrless \frac{\partial i_h}{\partial T}$ no evidence if $\frac{\partial f(i_l)}{\partial T} > \frac{\partial f(i_h)}{\partial T} \Rightarrow \frac{\partial i_l}{\partial T} > \frac{\partial i_h}{\partial T}$ reject 4a and coherent with 4b

Table 3: C-section rates and patient distributions across hospital types in our sample.

		Hospital type		
		PUBLIC	**PRIVATE**	**TOTAL**
C-section rates	1997	25.4%	23.3%	25.3%
	1998	25.7%	30.3%	25.9%
	Pooled	25.6%	26.6%	25.6%
Market shares				
	1997	95.0%	5.0%	100.0%
	1998	95.5%	4.5%	100.0%
	Pooled	95.3%	4.7%	100.0%

Table 4: Variable description

Mnemonics	Description
Age25	=1 if the woman is younger than 25; =0 otherwise
Age36	=1 if the woman is older than 36; =0 otherwise
Prior*	=1 if the woman had a previous c-section; =0 otherwise
Breech**	=1 if the woman presents breech, malpresentation, or malposition; =0 otherwise
Previous	=1 if the woman was admitted to hospital within 90 days from delivery; =0 otherwise
Cesarean	=1 if the woman delivers with c-section =0 otherwise
Private	=1 if the woman is admitted to private hospital =0 otherwise
Fee change (d98)	=1 if the woman delivers her baby after the fee change (1998) =0 otherwise
Age	Age of the woman
Agesq	Age squared/100
Distance 1	Minimum distance (in km.) from homeplace to public hospital
Distance 2	Minimum distance (in km.) from homeplace to private hospital
Travelled dist.	Distance (in km.) from homeplace to admitting hospital
Car	% of high powered car in the residing town
Hill	=1 if the town lies 200 meters above the sea level =0 otherwise
Not Bologna	=1 if woman does not reside in the main town (Bologna) =0 otherwise
Population	Number of inhabitants of the residing town/1000
Populationsq	Pop squared/1000
Mean income	Mean gross income in the residing town/1000 italian lira
Elderly	% of elderly (>65) in the population of the residing town

*Prior cesarean is indicated in the hospital discharge record by ICD-9 codes of 654.2x, "uterine scar from previous surgery". **Breech, other malpresentation, or malposition is indicated in the discharge record by ICD-9 diagnosis codes of 652.xx or procedure codes 72.5x [see Keeler, et al. 1997].

Table 5: Simultaneous probit model

Variables	Coefficient	Stand. error	Significance	Coefficient	Stand. Error	Significance
	Cesarean section equation			Cesarean section equation		
Age25	-0.29275	0.08283	♦♦♦			
Age36	0.25401	0.05493	♦♦♦			
Agedum				0.26591	0.04241	♦♦♦
Prior	2.11227	0.09389	♦♦♦	2.11457	0.09393	♦♦♦
Breech	2.52396	0.13846	♦♦♦	2.52347	0.13830	♦♦♦
Previous	0.25634	0.05192	♦♦♦	0.25583	0.05191	♦♦♦
Private	-0.02647	0.19959		-0.01570	0.18986	
Age25*Private	0.38196	0.35983				
Age36*Private	-0.17643	0.24928				
Agedum*Private				-0.25202	0.19648	
Previous*Private	0.55810	0.29595	♦	0.55114	0.29526	♦
Fee change	-0.02712	0.04035		-0.01848	0.03671	
Age25*Fee change	0.14975	0.11697				
Age36*Fee change	-0.06643	0.07866				
Agedum*Fee change				-0.09375	0.06107	
Prior*Fee change	0.08304	0.13368		0.07993	0.13379	
Breech*Fee change	0.02445	0.19405		0.02571	0.19358	
Previous*Fee change	0.02393	0.07347		0.02453	0.07347	
Private*Fee change	0.33862	0.17186	♦♦♦	0.33769	0.15433	♦♦♦
Age25*Private*Fee change	-0.38161	0.55044				
Age36*Private*Fee change	0.46061	0.37614				
Agedum*Private*Fee change				0.46294	0.30646	
Previous*Private*Fee change	-0.56633	0.43242		-0.57337	0.43006	
Constant	-1.00873	0.02944	♦♦♦	-1.01198	0.02675	♦♦♦
	Hospital choice equation			Hospital choice equation		
Age	0.10521	0.06965		0.12055	0.05210	♦♦♦
Age Sq	-0.17267	0.11105		-0.18761	0.08328	♦♦♦
Prior	0.05895	0.13634		-0.03330	0.10102	
Breech	0.10970	0.15201		0.09624	0.11205	
Previous	-0.37481	0.09978	♦♦♦	-0.36820	0.07349	♦♦♦
Pop*NB	-0.09789	0.01508	♦♦♦	-0.09663	0.01165	♦♦♦
PopSq*NB	1.68212	0.20612	♦♦♦	1.68882	0.15831	♦♦♦
Distance 1	0.00274	0.00471		0.00136	0.00336	
Distance 2	-0.00729	0.00470		-0.00810	0.00370	♦♦♦
Hill	-0.52277	0.21026	♦♦♦	-0.46862	0.16333	♦♦♦
Car*NB	19.90589	8.09944	♦♦♦	20.48587	5.92265	♦♦♦
NB	0.44347	0.38204		0.36253	0.28727	
Age*Fee change	0.04702	0.10415				
Age Sq*Fee change	-0.05215	0.16642				
Prior*Fee change	-0.21149	0.20197				
Breech*Fee change	-0.02925	0.22394				
Previous*Fee change	0.00193	0.14750				
Pop*NB*Fee change	0.00268	0.02382				
PopSq*NB*Fee change	0.02091	0.32323				
Distance 1*Fee change	-0.00224	0.00655				
Distance 2*Fee change	-0.00220	0.00758				
Hill*Fee change	0.11916	0.33490				
Car*NB*Fee change	2.66297	11.86929				
NB*Fee change	-0.22516	0.58101				
Fee change	-0.94711	1.61567				
Constant	-3.47532	1.08471	♦♦♦	-3.80363	0.80815	♦♦♦
$\hat{r}_{12}$	-0.07288	0.08852		-0.06478	0.08739	
Number of observations	10343			10343		
Zero outcomes	7643					
Nonzero outcomes	2700					
Log likelihood	-6066.877			-6073.27		

♦ ♦ ♦, ♦ ♦, ♦ denote significance at 1%, 5% and 10% levels respectively.

Table 6: probit model estimates – c-section equation

Variables	Coefficient	Stand. error	Significance
Agedum	0.21937	0.03052	♦♦♦
Prior	2.15452	0.06684	♦♦♦
Breech	2.53733	0.09675	♦♦♦
Previous	0.26583	0.03675	♦♦♦
Private	-0.13537	0.11079	
Agedum*Private	-0.21564	0.19440	
Previous*Private	0.52302	0.29259	♦♦
Fee change	-0.01823	0.03047	
Private*Fee change	0.35045	0.15336	♦♦♦
Agedum*Private*Fee change	0.35421	0.29867	
Previous*Private*Fee change	-0.54598	0.42317	
Constant	-1.006	0.02376	♦♦♦
Number of observations	10343		
Zero outcomes	7643		
Nonzero outcomes	2700		
Wald $chi^2(10)$	1759.71		
Log likelihood	-4525.27		
Prob > chi^2	0.000		
Pseudo R^2	0.238		

Misspecification Test	t-statistic
Omitted variables	
Elderly index	0.9449
Mean income	-0.2656
Travelled Distance	0.6159
Car*NB	-0.1150
NB	-0.0367
Normality	
Square predict.	-1.4325
Cubic predict.	-1.7125
Heteroscedasticity	
Agedum	0.5994
Age	-0.4030
Agesq	-0.5567
Prior	-1.6345
Breech	-0.3393
Previous	-2.4195
Private	-0.2045
Fee change	-0.2982
Private*Fee change	-0.7455
Travelled Distance	-0.9146

♦♦♦, ♦♦, ♦ denote significance at 1%, 5% and 10% levels respectively.

Table 7a: Predicted c-section probabilities and test statistic on probabilities change: implication 2.

HOSPITAL	Risk Class	PUBLIC Fixed budget	PRIVATE Tariffs	DIFFERENCE	TEST
1997	1	0.157	0.127	-0.030	-1.307
	2	0.875	0.845	-0.030	-1.144
	3	0.914	0.845	-0.069	-1.477
	4	0.937	0.919	-0.019	-1.101
1998	1	0.153	0.209	0.056	1.852
	2	0.871	0.911	0.040	2.247
	3	0.911	0.956	0.044	1.931
	4	0.935	0.958	0.023	2.267

Table 7b: Predicted c-section probabilities and test statistic on probabilities change for hospital financed through tariffs: implication 3a.

Risk Class	1997	1998	$\frac{\partial f(i_r)}{\partial T}$	TEST	% increase
1	0.127	0.209	-0.412	-2.198	65%
2	0.845	0.911	-0.331	-2.127	8%
3	0.845	0.956	-0.552	-2.139	13%
4	0.919	0.958	-0.197	-2.007	4%

Table 7c: Predicted c-section probabilities and test statistic on probabilities change for hospital financed through tariffs: implication 4.

	1	2	3
2	-0.016		
	-1.129		
3	0.028	0.044	
	0.505	*0.857*	
4	-0.043	-0.027	-0.071
	-1.913	*-1.871*	*-1.420*

* Risk class=4 refers to a woman with age between 25 and 36 and breech presentation; risk class=3 refers to a woman with age>36 and with a prior cesarean; risk class=2 refers to a woman with age between 25 and 36 and a prior cesarean; finally, risk class=1 refers to a woman with no risk factor. Classes account for 52.7% (class 1), 3.3% (class 2), 1.6% (class 3), 2.6% (class 4) of the sample.