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# Social interactions in inappropriate behavior for childbirth services: Theory and evidence from the Italian hospital sector

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*Over the last decades the role of social interactions has become increasingly important in the economic discussion and, by now, it is acknowledged that the interaction across agents can produce both positive and negative effects. In this paper we evaluate the role of social interactions in the hospital sector using the large incidence of cesarean section, usually considered an inappropriate outcome in the childbirth service. In doing so, we lay out a theoretical model of hospitals' behavior where the effect of peers' behavior emerges by the simple sharing of the same institutional authority. Then, using the risk adjusted cesarean section rate of a large panel of Italian hospitals, we empirically investigate whether the behavior of each hospital is affected by the behavior of hospitals within the same region, after controlling for demand, supply and financial factors. In particular, we perform our empirical test employing both peer effects estimate and the spatial econometric approach, exploiting the panel dimension of our data. Both estimates show a significant and strong presence of peer effects among hospitals, robust to sensitivity analyses. We interpret this evidence as a large presence of constraint interactions in the healthcare sector, with important implications for the healthcare policy.*

JEL Classification: I11, C31

Keywords: Social interactions, peer effects, caesarean section, spatial econometrics.

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## 1. Introduction

Over the last decades the role of social interactions has become increasingly important in the economic discussion. Even if the origin of social interactions can be found in the sociological literature (e.g., Crane, 1991; Mayer, 1991), by now it is acknowledged that the interaction across agents can produce both positive and negative effects. The economic literature in education, for instance, investigates the presence of positive effects in students' outcomes given by the interaction with their classmates (e.g., Epple and Romano, 1998; Sacerdote, 2001; Zimmerman, 2003). On the other hand, the interaction among peers can produce also negative effects, as found in crime (e.g., Glaeser et al., 1996), in tax evasion (e.g., Galbiati and Zanella, 2012) and in health behavior (e.g., Trogdon et al., 2008).

In this paper, we study the interesting case of high cesarean section rate in the Italian hospital sector. The recent worldwide upward trend in cesarean rates (OECD, 2011) has drawn the attention of both scholars and policymakers, raising concern about the clinically appropriateness of some cesarean deliveries. Furthermore, cesarean section rates exhibit an extraordinarily high variation among regions (e.g., Grant, 2005; Baicker et al., 2006), even after being adjusted for the risk. In particular, in absence of specific therapeutic reasons, the alternative vaginal delivery is generally considered a more appropriate (and less risky) medical treatment (e.g., Althabe et al., 2006; Betrán et al., 2007; Belizán et al., 2007). Moreover, medically unjustified cesarean deliveries have implications not only for patients but also for the overall society, as they impose a financial burden on the healthcare system, while diverting resources from other public interventions.

As far as the Italian case is concerned, about 38% of all child deliveries in Italy is performed via cesarean section, a percentage well beyond the WHO (1985) recommended level of 15%. In this regard, among others[1] a recent national report of the Italian Ministry of Health has concluded that 43% of the cesarean sections executed in 2010 appeared unjustified, based on the information included in the patients' discharge records. Not surprisingly, this percentage of inappropriateness would imply for the Italian National Health Service an increase in expenditures equal to 80-85 million euros per year[2].

Along with clinical factors, many explanations for high cesarean rates have been explored in the literature including maternal age (e.g. Abdul-Rahim et al., 2009), physician's

[1] See e.g., Fortino et al. (2002), Rusticali and Di Virgilio (2010).

[2] Available at: http://www.salute.gov.it/portale/news/p3_2_1_1_1.jsp?lingua=italiano&menu=notizie&p=dalministero&id=914

perception of the safety of the procedure (e.g., Hopkins, 2000; Kabakian-Khasholian et al., 2007), "defensive medicine" (e.g., Grant and McInnes, 2004; Dubay et al., 1999), social and cultural factors (e.g., Lo, 2003; Hsu et al., 2008), health system features (e.g., Lee and Lee, 2007; Nigam, 2012). However, all together these factors do not account for the majority of the observed variation. For this reason, many studies have investigated the hypothesis that providers are motivated by financial incentives in their choice of the child delivery method, finding that financial incentives play a significant role in explaining cesarean section rates (e.g., Gruber et al., 1999; Grant, 2009). Looking at the Italian case, in Cavalieri et al. (2014) it is found that whenever the regional reimbursement policy favors cesarean sections, regional providers have an incentive to shift deliveries away from natural childbirths to the more highly reimbursed surgical cesarean procedure.

The purpose of this paper is to study the presence of peer effects in the interesting case of high cesarean section rate in the Italian hospital sector. In particular, we investigate whether the behavior of each hospital is affected by the behavior of hospitals within the same region. To this extent, we develop firstly a model where the effect of peers' behavior emerges by the simple sharing of the same institutional authority. In fact, each region cannot afford to contrast the inappropriate behavior of all hospitals within the region; therefore, the inappropriate behavior of hospitals within a region make the open road to the inappropriate behavior of their peers. Subsequently, we test the main implication of the model and, in particular, the presence of peer effects in the Italian hospital sector, after controlling for demand, supply and financial factors. Indeed, the Italian NHS is an especially interesting case for testing such hypothesis, as decentralization processes have made the Regional Health Authorities (RHAs) the main institutional authorities for each hospital and, in particular, the reference third-party payers for the health services provided. Moreover, not only Italy exhibits one of the highest cesarean rates among the OECD countries but, as a result of the high decentralization, great variation exists across regions both in the regulation and in the delivery of childbirth services (e.g., Francese et al., 2014; Cavalieri et al., 2014).

As far as the empirical analysis is concerned, we perform first a more traditional peer effects estimate, really close to our microfounded model of hospitals' behavior. As will be shown, this is a particularly fortune case of peer effects analysis, since our non-linear model does not suffer for the "reflection problem" of the linear-in-mean models (e.g., Maski, 1993; Brock and Durlauf, 2007). Then, we carry out also the more recent (but, certainly, less microfounded) spatial econometric analysis, exploiting the panel dimension of our data.

Differently from the standard spatial analysis, however, the spatial weights matrix is not based on the geographic distance among hospitals; rather, it is based again on the sharing of the same institutional authorities, in line with a few contributions claiming the primary importance of institutions respect to geography (e.g., Rodrik et al., 2004; Arbia et al., 2009; Atella et al., 2014). Both estimates show a significant and strong presence of peer effects among hospitals, robust to sensitivity analyses. Following the classification proposed by Manski (2000), we interpret this evidence as a large presence of *constraint interactions* in the healthcare sector, with important implications for the healthcare policy.

The rest of the paper proceeds as follows. In Section 2 we lay out the model of hospitals' behavior and derive the main implication on peer effects. In Section 3 we describe our data, along with the Italian hospital payment system. The formal empirical strategy is presented in Section 4 and, then, results are reported in Section 5. Finally, Section 6 concludes with a discussion on the main implications for the healthcare policy.

## 2. The model

In this section we lay out a model of hospitals' behavior where the effect of peers' behavior emerges by the simple sharing of the same institutional authority. In the specific case under study, the behavior of hospitals consists in the selection among two competing treatments (that is, vaginal and cesarean section) for each patient, which will result in the hospital 's cesarean section rate. Following the previous literature on hospitals' behavior (e.g., Ellis and McGuire, 1986; Chandra et al., 2011), we assume that hospitals select treatments to maximize their objective function; therefore, the resulting cesarean section rate might not be the "appropriate" one for the healthcare system as a whole.

Consider a population of *N* risk neutral hospitals $i = 1, 2, \ldots, N$, distributed across *R* health institutional authorities $r = 1, 2, \ldots, R$ each of size $n_r$. Health authorities are the reference third-party payers for the health services provided by each hospital and, furthermore, they are in charge of the "appropriateness" of the healthcare system in each group *r*. However, they operate under a stringent budget constraint for their activity, implying that only a fraction of hospitals in each *r* can be audited by the reference health authority.

For each patient, hospitals choose between two competing treatments $\{0, 1\}$, where 0 is usually considered the most appropriate treatment in absence of specific therapeutic reasons[3]. Each treatment produces a different benefit $B(\sigma)$ for patients, according to the patient characteristics $\sigma$. In particular, the utility of patient *k* from the two treatments are given by[4]:

$$U_k(0) = B^0(\sigma_k) + \varepsilon_k^0 \tag{1}$$

$$U_k(1) = B^1(\sigma_k) + \varepsilon_k^1 \tag{2}$$

where the error terms capture heterogeneity in the benefits of each treatment to that patient, and follow a standard extreme value distribution, that is $\varepsilon^{0,1} \sim EV(0, 1)$. On the other hand, each treatment implies a different cost $C(\sigma, X)$, according to the patient characteristics $\sigma$ and the hospital characteristics $X$.

In the case hospital *i* would choose the appropriate treatment for patient *k*, he chooses treatment 1 over treatment 0 provided that the improved benefit compensates for the increased costs, that is:

$$\begin{aligned} Pr\{treat_{ik} = 1\} &= Pr\{B^1(\sigma_k) - \lambda C^1(\sigma_k, X_i) + \varepsilon_k^1 > B^0(\sigma_k) - \lambda C^0(\sigma_k, X_i) + \varepsilon_k^0\} = \\ &= Pr\{[B^1(\sigma_k) - B^0(\sigma_k)] - \lambda[C^1(\sigma_k, X_i) - C^0(\sigma_k, X_i)] + \xi_k > 0\} = \\ &= Pr\{\xi_k < [B^1(\sigma_k) - B^0(\sigma_k)] - \lambda [C^1(\sigma_k, X_i) - C^0(\sigma_k, X_i)]\} = \\ &= \frac{e^{[B^1(\sigma_k) - B^0(\sigma_k)] - \lambda [C^1(\sigma_k, X_i) - C^0(\sigma_k, X_i)]}}{1 + e^{[B^1(\sigma_k) - B^0(\sigma_k)] - \lambda [C^1(\sigma_k, X_i) - C^0(\sigma_k, X_i)]}} \end{aligned} \tag{3}$$

where we have exploited the fact that $(\varepsilon_k^1 - \varepsilon_k^0) = \xi_k \sim Logistic(0, 1)$. The parameter $\lambda$ in (3) is usually called the *value of life* and captures the trade-off made by third-party payer between improved benefit and increased costs (e.g., Murphy and Topel, 2006). Equation (3) represents the probability for patient *k* of getting treatment 1 in hospital *i*. Therefore, integrating (3) over the distribution $f(\sigma)$ of patient characteristics $\sigma$ produces the appropriate cesarean section rate of hospital *i*:

$$CS_i^{app} = \int_\sigma \left\{ \frac{e^{[B^1(\sigma_k) - B^0(\sigma_k)] - \lambda [C^1(\sigma_k, X_i) - C^0(\sigma_k, X_i)]}}{1 + e^{[B^1(\sigma_k) - B^0(\sigma_k)] - \lambda [C^1(\sigma_k, X_i) - C^0(\sigma_k, X_i)]}} \right\} f(\sigma)\, d\sigma \tag{4}$$

As we stated above, however, hospitals select treatments to maximize their objective function. Following the previous literature (e.g., McGuire and Pauly, 1991; Chandra et al.,

[3] As we discussed above, in our specific case the vaginal birth is usually considered a more appropriate treatment (e.g., Althabe et al., 2006; Betrán et al., 2007; Belizán et al., 2007), not only for medical reasons but also because unjustified cesarean deliveries impose an heavier financial burden on the healthcare system.

[4] Notice that we are implicitly assuming that patients do not pay any price for the health service they get; or, alternatively, they pay exactly the same price regardless what treatment they get, which is essentially the Italian case.

2011), while hospitals contemplate the benefit of each treatment to their patients, they also consider explicitly the financial incentives associated with the two treatments. In particular, the welfare of hospital *i* from providing the two treatments to patient *k* are given by:

$$W_{ik}(0) = \beta_i B^0(\sigma_k) + V^0(F_r^0) - C^0(\sigma_k, X_i) + Z_r^0 + \varepsilon_k^0 \tag{5}$$

$$W_{ik}(1) = \beta_i B^1(\sigma_k) + V^1(F_r^1) - C^1(\sigma_k, X_i) + Z_r^1 + \varepsilon_k^1 \tag{6}$$

where $\beta_i$ reflects the relative importance of patient benefit respect to financial aspects, $V(F)$ capture the expected revenues from the two treatments as a function of fees and, finally, $Z$ are other contextual factors affecting hospitals in each group *r*. Specifically, whenever hospitals claim for a treatment 0 (usually considered the most appropriate), they always get the established fee, that is $V^0(F_r^0) = F_r^0$. Differently, whenever hospitals claim for a treatment 1, what they get is conditional on being audited by the reference third-party payer. In particular, when hospital *i* is not audited, then *i* gets $F_r^1$ for each claim. Instead, when hospital *i* is audited, then *i* receives a reduction in fee proportional to the "inappropriate" claims. Therefore, the expected revenue from a treatment 1, in each group *r*, is given by:

$$V^1(F_r^1) = (1 - p_{ir})\, F_r^1 + p_{ir} \min\left\{1, \frac{CS_i^{app}}{CS_i^*}\right\} F_r^1 \tag{7}$$

where $p_{ir}$ is the probability for hospital *i* of being audited by the reference third-party payer *r*. Reasonably, if hospital *i* claims an appropriate share of treatment 1 (that is, $CS_i^* \leq CS_i^{app}$)[5], according to (7) he does not receive any reduction in fees. On the other hand, if $CS_i^* > CS_i^{app}$ then hospital *i* might be subjected to the reduction if audited.

As we said above, each health authority operates under a stringent budget constraint, implying that each hospital is audited only with some positive probability *p*. However, the probability of being audited is not fully random, as the behavior of hospitals within each group *r* gives already an information to the health authority. For the sake of simplicity, we assume the following linear specification that captures the effect of hospitals' behavior within the same group *r* on hospital *i*'s audit probability:

$$p_{ir} = \frac{n_r^{control}}{n_r} + \gamma Pr\left(CS_i^* > CS_i^{app} \middle| CS_i^*\right) - \frac{\theta}{n_r - 1} \sum_{j \in r, j \neq i} Pr\left(CS_j^* > CS_j^{app} \middle| CS_j^*\right) \tag{8}$$

[5] Since $F_r^1 > F_r^0 \;\; \forall\, r \in R$ (that is, caesarean section fees are higher than vaginal fees), there should be no incentive for hospitals to claim $CS_i^* < CS_i^{app}$, as the profit associated with cesarean sections is usually higher than that associated with vaginal delivery. Certainly, this is the case for hospitals in the Italian NHS (e.g., Francese et al., 2014; Cavalieri et al., 2014).

The first term of (8) is the random probability of being audited, equal to the fraction of hospitals the health authority $r$ can afford to audit, with $n_r^{control} < n_r$ because of the stringent budget constraint. The other terms, instead, capture the idea that health authorities somehow infer the probability of inappropriate claims from hospitals' behavior (that is, from $CS^*$) and, accordingly, shift audit resources toward more suspicious hospitals. Indeed, we do not want to model explicitly the way in which health authorities estimate the probability of inappropriate claims, as it might even be different across *r*; nonetheless, it is certainly reasonable simply to assume that higher is the amount of claims for treatment 1, higher is the estimated probability of inappropriate claims, that is:

$$\frac{\partial Pr(CS_i^* > CS_i^{app} | CS_i^*)}{\partial CS_i^*} > 0 \qquad \forall\ i \in r,\ \forall\ r \in R \tag{9}$$

Interestingly, as long as $CS_i^* > CS_i^{app}$, (9) it is enough to imply that:

$$\frac{\partial V^1(F_r^1)}{\partial CS_i^*} = \left(\frac{CS_i^{app}}{CS_i^*} - 1\right) F_r^1 \frac{\partial Pr(CS_i^* > CS_i^{app} | CS_i^*)}{\partial CS_i^*} - F_r^1\, p_{ir} \frac{CS_i^{app}}{CS_i^{*2}} < 0 \tag{10}$$

$$\frac{\partial V^1(F_r^1)}{\partial CS_{j \in r, j \neq i}^*} = \left(1 - \frac{CS_i^{app}}{CS_i^*}\right) F_r^1 \frac{\theta}{n_r - 1} \frac{\partial Pr\left(CS_j^* > CS_j^{app} \middle| CS_j^*\right)}{\partial CS_j^*} > 0 \tag{11}$$

Therefore, when other hospitals within the same group *r* become more suspicious for the health authority operating under a stringent resource constraint, this will produce the effect of reducing the hospital *i*'s probability of being audited and, in turn, will increase the expected value of a marginal inappropriate claim. In other words, the last term of (8) represents the effect of peers' behavior on the other hospitals sharing the same institutional authority.

Differently from the previous case (3), hospital *i* chooses treatment 1 over treatment 0 for patient *k* provided that $W_{ik}(1) > W_{ik}(0)$ , that is:

$$\begin{aligned} Pr\{treat_{ik} = 1\} &= Pr\{W_{ik}(1) > W_{ik}(0)\} = Pr\{I_{ik}(1) + \varepsilon_k^1 > I_{ik}(0) + \varepsilon_k^0\} = \\ &= Pr\{I_{ik}(1) - I_{ik}(0) + \xi_k > 0\} = Pr\{\xi_k < I_{ik}(1) - I_{ik}(0)\} = \\ &= \frac{e^{[I_{ik}(1) - I_{ik}(0)]}}{1 + e^{[I_{ik}(1) - I_{ik}(0)]}} \end{aligned} \tag{12}$$

with $I_{ik} = \beta_i B(\sigma_k) + V(F_r) - C(\sigma_k, X_i) + Z_r$ and $(\varepsilon_k^1 - \varepsilon_k^0) = \xi_k \sim Logistic(0,1)$. Then, integrating (12) over the distribution $f(\sigma)$ of patient characteristics $\sigma$, we obtain:

$$CS_i^* = \int_\sigma \left\{\frac{e^{[I_{ik}(1) - I_{ik}(0)]}}{1 + e^{[I_{ik}(1) - I_{ik}(0)]}}\right\} f(\sigma)\, d\sigma \equiv G(CS_i^*) \tag{13}$$

Notice that (13) represents the hospital $i$' s reaction function (as a fixed point), since it tells us the optimal cesarean section rate as a function of all other hospitals (within $r$) cesarean section rates. Interestingly, from (10) we have that:

$$\frac{\partial G(CS_i^*)}{\partial CS_i^*} = \frac{\partial V^1(F_r^1)}{\partial CS_i^*} \int_\sigma \left\{ \frac{e^{[I_{ik}(1)-I_{ik}(0)]}}{\left( \left[1+e^{[I_{ik}(1)-I_{ik}(0)]}\right]^2 \right)} \right\} f(\sigma)\, d\sigma \begin{cases} < 0 & if \quad CS_i^* > CS_i^{app} \\ = 0 & if \quad CS_i^* \leq CS_i^{app} \end{cases} \tag{14}$$

Therefore, as shown in Figure (1), (13) gives a unique $CS_i^*$ best response:

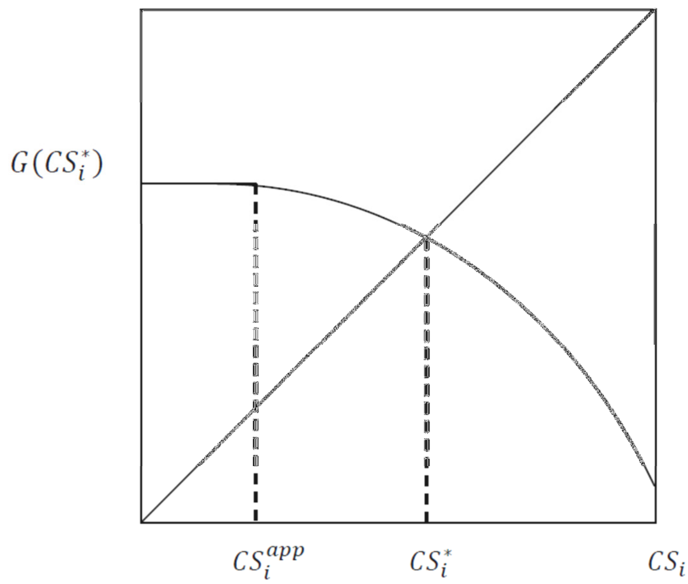


**Figure 1. Optimal $CS_i^*$ best response**

Moreover, applying the implicit function theorem to the equilibrium condition (13), we have the main implication of the model concerning the presence of peer effects on hospitals' inappropriate behavior, that is:

$$\frac{\partial CS_i^*}{\partial CS_{j\in r, j\neq i}^*} = -\frac{\partial D\left(CS_i^*, CS_{j\in r,j\neq i}^*\right)/\partial CS_{j\in r,j\neq i}^*}{\partial D\left(CS_i^*, CS_{j\in r,j\neq i}^*\right)/\partial CS_i^*} > 0 \tag{15}$$

where we have posed the equilibrium condition (13) in the implicit form:

$$D\left(CS_i^*, CS_{j\in r,j\neq i}^*\right) = CS_i^* - \int_\sigma \left\{ \frac{e^{[I_{ik}(1)-I_{ik}(0)]}}{1+e^{[I_{ik}(1)-I_{ik}(0)]}} \right\} f(\sigma)\, d\sigma \tag{16}$$

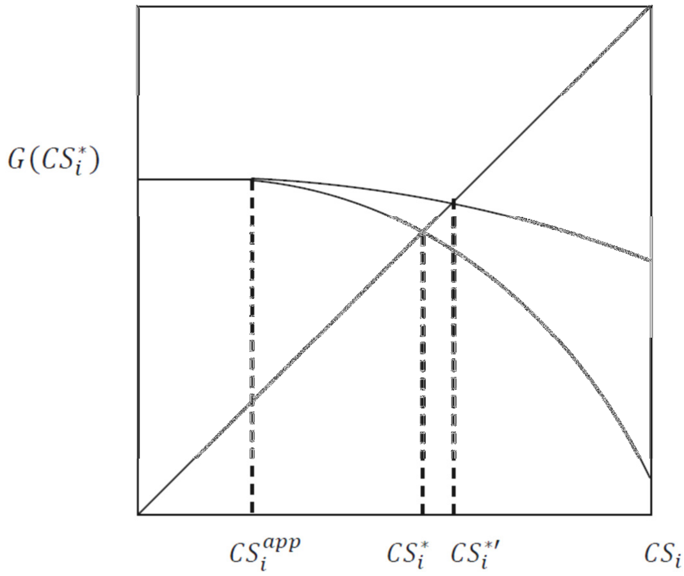


**Figure 2. Peers effect on equilibrium $CS_i^*$**

The effect of peers' behavior on the hospital *i*'s cesarean section rate is shown also in Figure (2). Again, the main intuition of (15) is that, once other hospitals within *r* exhibit higher cesarean section rate, they become relatively more suspicious in the eye of the reference health authority *r*, which accordingly will shift more audit resources toward them. In other words, peers with higher cesarean section rates will reduce the hospital's probability of being audited and, in turn, will increase the expected value of inappropriate claims.

Regardless the extent of peer effects[6], the model has a unique Nash equilibrium (as a fixed point) with many interesting empirical implications. Firstly, our model has the important empirical implication that the inappropriate behavior of hospitals and, in particular, the cesarean section rate should turn out to be spatially correlated not much according to the geographic distance among peers, but rather according to the sharing of the same institutional authority. Indeed, this view of peer effects among hospitals' behavior is somewhat different respect to the usual interpretation of learning from the reference school treatment style (e.g., Epstein and Nicholson, 2009). Secondly, the presence of peer effects should generate an excess variance in equilibrium, meaning that even a small difference in fundamentals among hospitals (belonging to different institutional authorities) might produce large differences in

[6] Linear-in-mean models would need a stability requirement on the magnitude of peer effects, such as the impact of peers' behavior on the probability of being audited $\theta$ has to be somewhat lower than the impact of own behavior $\gamma$ (e.g., Galbiati and Zanella, 2012). Provided that probabilities are well-behaved, in our non-linear-in-mean model such requirement is not needed for guarantee a unique Nash equilibrium, as the equilibrium would converge in any case, as can be gathered from Figure 2. Nonetheless, this restriction on the magnitude of peer effects remains certainly reasonable also in our context and, in particular, we will see below that estimated marginal peer effects are strictly less than 1 in all estimates.

cesarean section rates. Therefore, peer effects would contribute to explain the large regional variation in health services not explained by differences in fundamentals (e.g., Skinner, 2011).

Looking briefly at the other implications of the model, indeed these are more standard in the literature on hospitals' behavior (e.g., Chandra et al., 2011). In particular, to the extent that different hospital types (e.g., private *vs.* public) might evaluate patients utility differently in their objective function (that is, $\beta_i \neq \beta_j$), they could exhibit different equilibrium cesarean section rates. Similarly, those institutional authorities with a higher fee differential (that is, $F_r^1 - F_r^0 > F_l^1 - F_l^0$) could have hospitals with higher equilibrium cesarean section rates. Finally, as long as the provision of childbirth services is characterized by economies of scale and/or *learning-by-doing* effects, hospitals with different characteristics and/or different degree of specialization (that is, $C^{0,1}(\sigma_k, X_i) \neq C^{0,1}(\sigma_k, X_j)$) could also exhibit different equilibrium cesarean section rates, *ceteris paribus*.

To some extent, the described process generating peer effects among hospitals is fairly similar to models of enforcement congestion developed in other strand of literature as crime behavior (e.g., Sah, 1991) and tax evasion (e.g., Galbiati and Zanella, 2012). Respect to those contexts, however, our model presents the significant advantage that each hospital can have a rather limited number of peers within the reference group, making more reasonable the idea that agents somehow guess the probability of being audited by the reference health authority after observing the behavior of their peers.

An important feature of our model deserving more discussion is that, indeed, we are emphasizing only one source of social interaction (that is, *constrain interactions* within the same health authority), whereas potentially other social forces may be at work. Nonetheless, we have good reasons to do so in our context. Firstly, the usual argument that wide inappropriate behaviors violate social norms, whose strength decreases with the diffusion of such behavior within the reference group, does not seem to play a role in our context, as high cesarean rate is not necessarily view negatively among patients (e.g., Grant, 2005; Fusco et al., 2010). Similarly, previous literature on physicians' learning from the reference school treatment style (a potential source of *preference interactions* among peers) shows that physicians do not change significantly their style on childbirth treatment due to local peer interactions (e.g., Epstein and Nicholson, 2009). Moreover, a considerable number of studies emphasizes that higher tariff differentials among alternative treatments induce hospitals to shift deliveries toward the more highly reimbursed procedure (e.g., Grant, 2009; Cavalieri et al., 2014); thus, it seems fairly reasonable to investigate whether peers' behavior within the reference institutional authority represents a significant constraint for hospitals' inappropriate behavior. Finally, the source of social interaction emphasized in our paper identifies exogenously the reference group for each hospital, instead of being the outcome of an arbitrary choice of the researcher. Indeed, this should represent a significant advantage of our model, especially for the subsequent empirical analysis, as it is well-known that wrong assumptions on reference groups could be strongly misleading (e.g., Conley and Topa, 2003).

## 3. Data description

The main source of data for our empirical analysis is the National Program for Outcome Assessment (*PNE - Programma Nazionale Valutazione Esiti*) run by the National Agency for Regional Health Services (*AGENAS - Agenzia Nazionale per i Servizi Sanitari Regionali*) together with the Italian Ministry of Health. Since its inception in 2009, the program has aimed at assessing the health care activity of all Italian hospitals, either public or private accredited. Overall, 45 performance indicators (32 related to hospital services and 13 to hospitalization) are computed, mostly using discharge data gathered through the Informative Hospital System (*SIO - Sistema Informativo Ospedaliero*)[7].

One of the outcome indicators provided by the *PNE* is the risk-adjusted cesarean rate for first-time mothers, aged 10-55 years, who reside in Italy. Compared to the overall rate of cesarean deliveries, this indicator is considered better suited to capture the phenomenon of clinical inappropriateness, since it is not strongly influenced by the high risk of cesarean delivery for those women who already experienced a cesarean section and by their distribution among hospitals. The cesarean rate for first-time mothers provided by the *PNE* is adjusted for maternal age and comorbidities (main and secondary diagnoses for admissions during the last two years) as well as for a-priori fetus risk factors[8]. Our final sample consists of 2952 observations from 492 hospitals, over the period 2007-2012. Supply indicators for the structural characteristics of providers (number of beds, yearly birth deliveries, hospital type), published by the Italian Ministry of Health, are also considered in our analysis. Among the demand factors potentially relevant, we consider the female employment rate at the province level, provided by the Italian National Institute of Statistics (*ISTAT*). Summary statistics for these and other variables used in the analysis are reported in Table 1.

[7] For more information on PNE see *http://151.1.149.72/pne11_new*.

[8] Risk adjusted cesarean rates for first time mothers are reported by the *PNE* only for those hospitals with at least 10 childbirths in the selected year.

**Table 1 – Descriptive statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Risk-adj. cesarean rate for first-time mothers | 2952 | 0.31 | 0.16 | 0.03 | 0.94 |
| Vaginal birth fee (W CC) (in euro) | 120 | 2280.18 | 416.08 | 1370 | 3180 |
| Cesarean section fee (W CC) (in euro) | 120 | 3588.74 | 647.66 | 2316 | 4955 |
| FEEDIFF | 120 | 1.01 | 0.14 | 0.67 | 1.42 |
| Female employment rate | 654 | 47.21 | 11.74 | 22.71 | 64.82 |
| Number of beds | 2952 | 397.97 | 328.54 | 25 | 1719 |
| Number of births | 2952 | 830.97 | 662.85 | 90 | 7313 |

*Note*: FEEDIFF is the index of fee differential between cesarean and vaginal DRG tariffs W CC.

As shown in Figure 3, a first look at the data reveals great regional variability in cesarean section rates for first-time mothers in Italy. At the regional level, the risk-adjusted cesarean rate varies between a minimum of 14.6% in Alto Adige and a maximum of 50.1% in Campania, with an average national value of 31%. More specifically, cesarean rates are higher in southern regions (42.7% on average) than in the rest of the country (23% on average), as clearly emphasized by Figure 3. At the hospital level, variation in cesarean rates ranges from almost 3.2% in Lombardy to 94.5% in Lazio.

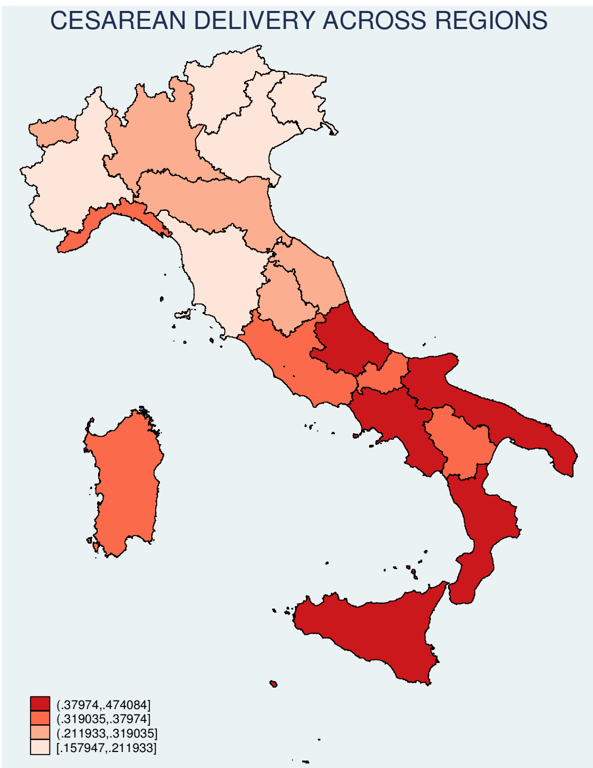


**Figure 3. Cesarean delivery for first-time mothers across Italian regions**

To shed a first light on the presence of peer effects among hospitals belonging to the same RHAs, in Figure 4 we plot hospital risk-adjusted cesarean section rates against the average cesarean rate of their peers. Despite the significant heterogeneity probably due to the different hospital types in the Italian NHS, fitted values would seem to reveal a positive relationship between hospital cesarean rates and the (inappropriate) behavior of their peers belonging to the same RHAs. In particular, in our dataset the correlation coefficient among the two above-mentioned variables is equal to $\rho = 0.67^{***}$. As clear, we cannot interpret this evidence as decisive, because the correlation in Figure 4 might potentially be spurious; nonetheless, this first evidence, along with the predictions of our theoretical model, give us the right motivation to carry on with the following empirical analysis.

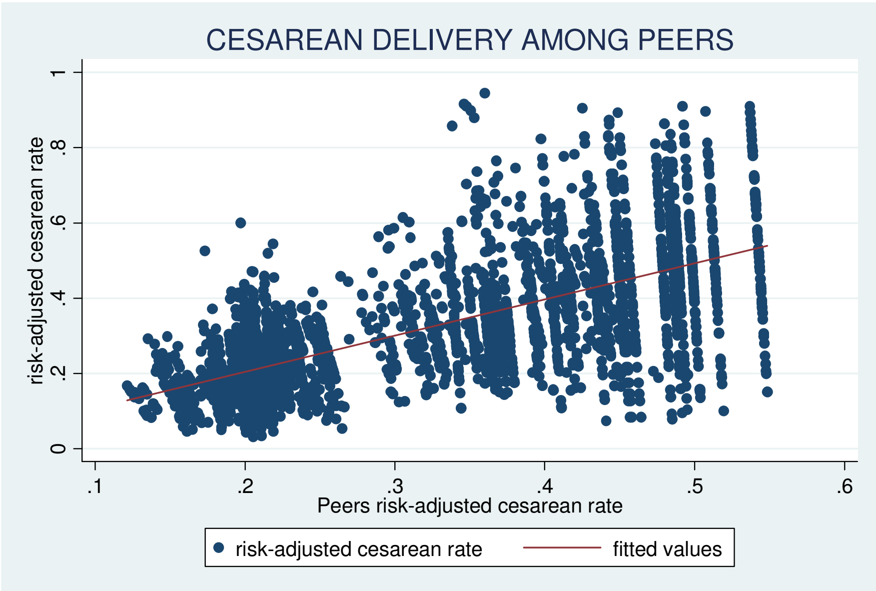


**Figure 4. Cesarean section rates and correlation among hospital peers**

As far as the typology of hospitals is concerned, as expected, the directly managed public hospitals (Hospital Units) display a lower median value of the risk-adjusted cesarean rate as well as a smaller variability of values (Figure 5). Not surprisingly, the opposite is true for private hospitals (Private Hospitals), displaying remarkably the higher median cesarean rate. Looking at the other categories of public hospitals, that is independent (Hospital Trusts) and research (Research Hospitals) hospitals, the latter show a higher median value but a smaller variability of risk-adjusted cesarean rates. Overall, it is evident from Figure 5 that there is a great variability in cesarean section rates also across providers, which should explain in part the high heterogeneity emerging in Figure 4.

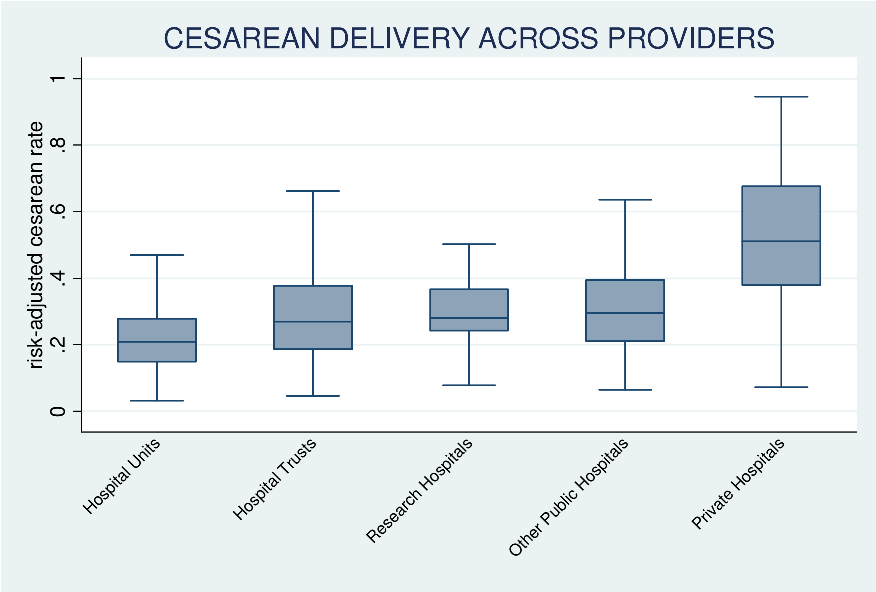


**Figure 5. Cesarean delivery for first-time mothers across providers**

In regard to regional payment policies for childbirth deliveries, we match information coming from several sources, mainly from the *AGENAS* but also directly from RHAs. We consider tariffs for ordinary admissions (longer than one day) for two specific DRGs (Medical Disease Classification 14), namely DRG 370 (cesarean section with complications and comorbidities) and DRG 372 (vaginal delivery with complications)[9], for each RHA in the years 2007-2012. In fact, the deep decentralization process carried out in the last decades not only have made Italian regions the reference third-party payers for the health care services provided by hospitals, but also have significantly increased the powers and responsibilities of RHAs in both the financing and delivery of health care. To this extent, each RHA is free either to apply the national tariffs or to set their own fees for childbirth deliveries. As shown in Table 1, tariffs for cesarean sections are on average higher than those for vaginal deliveries, due to the fact that the former is a surgical intervention, which should be performed in an operating room and by a surgeon. Even higher tariffs are, then, set for childbirth deliveries in presence of complications and comorbidities.

[9] Indeed, we might consider also the two DRG tariffs for childbirth deliveries without complications and comorbidities, namely DRG 371 (cesarean section without complications and comorbidities) and DRG 373 (vaginal delivery without complications). However, in Cavalieri et al. (2014) it is found that only DRG tariffs with CC are significant in driving providers' behavior, probably because of the greater difficulty for providers to "induce" and justify a cesarean delivery in absence of complications and comorbidities. In any case, it is difficult to disentangle the effect between the DRG tariff differential with CC and without CC, because in the Italian NHS they tend to be highly correlated (e.g., Cavalieri et al., 2014).

In particular, in our empirical analysis we consider the following tariff differential indicator, aiming to capture the relative financial convenience to compute cesarean sections in each region:

$$FEEDIFF = \frac{(RegFEE_{DRG370}/RegFEE_{DRG372})}{(NatFEE_{DRG370}/NatFEE_{DRG372})}$$

In line with our theoretical model (see the equilibrium $CS^*$ (13)), the idea behind this tariff indicator is that hospital cesarean rates are driven more by the DRG tariff differentials than by the amount of each DRG tariff. Therefore, the higher the regional tariff differential between cesarean and vaginal deliveries, the greater the incentive for regional providers to behave strategically by opting for a cesarean section[10], *ceteris paribus*. More specifically, a value of 1 of *FEEDIFF* indicates that a RHA has applied the same tariffs as the national ones for both cesarean and vaginal deliveries. Differently, a value higher (lower) than 1 designates a RHA where the ratio between the two DRG tariffs is higher (lower) than the corresponding national one, implying a relative financial convenience to execute a cesarean section. Figure 6 provides an overview of *FEEDIFF* by region for the last year in our sample, from which we can see that different RHAs in Italy have opted for different tariff policies.

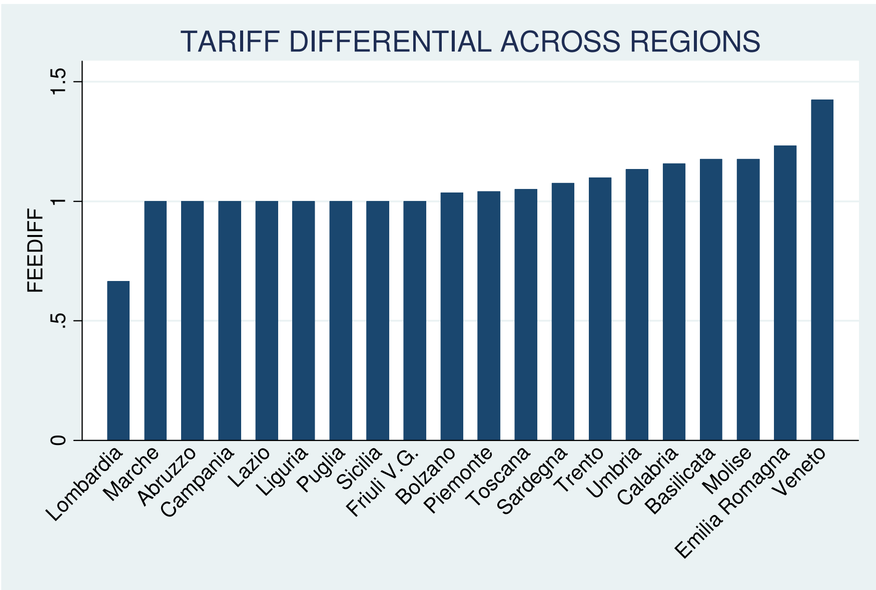


**Figure 6. Tariff differential indicator across Italian regions**

[10] By asserting this, we are implicitly assuming that costs are relatively homogeneous at the national level, at least among the same type of providers, which seems quite reasonable in the Italian context.

In the following, employing the described explanatory variables, we aim at testing whether our model prediction of significant peer effects among hospitals belonging to the same institutional authority is supported by the empirical evidence from the Italian hospital sector, after controlling for demand, supply and financial factors.

## 4. Empirical strategy

In this section we present the formal empirical strategy to test the presence of peer effects in cesarean section rates among Italian hospitals. Specifically, we perform first a more traditional peer effects estimate, really close to our microfounded model of hospitals' behavior. Then, we carry out also the more recent (but, certainly, less microfounded) spatial econometric analysis, exploiting the panel dimension of our data.

### 4.1 Logit model

Moving from the equilibrium condition (13) of our model, we estimate the following Logit model for the risk-adjusted caesarean rates:

$$RACR_{irkt} = \frac{e^{\left[\beta * Dem_{irt} + \tau * Bed_{irkt} + \gamma * Birth_{irkt} + \delta * FEEDIFF_{rt} + \rho \frac{\sum_{j \in r, j \neq i} RACR_{jrkt}}{n_r - 1} + \theta_k + \varphi_r + \mu_t\right]}}{1 + e^{\left[\beta * Dem_{irt} + \tau * Bed_{irkt} + \gamma * Birth_{irkt} + \delta * FEEDIFF_{rt} + \rho \frac{\sum_{j \in r, j \neq i} RACR_{jrkt}}{n_r - 1} + \theta_k + \varphi_r + \mu_t\right]}}$$

that is

$$Logit\ RACR_{irkt} = \alpha + \beta * Dem_{irt} + \tau * Bed_{irkt} + \gamma * Birth_{irkt} + \delta * FEEDIFF_{rt} +$$

$$+ \rho \frac{\sum_{j \in r, j \neq i} RACR_{jrkt}}{n_r - 1} + \theta_k + \varphi_r + \mu_t + \varepsilon_{irkt} \tag{17}$$

The dependent variable *RACR* is the risk-adjusted cesarean rate in hospital *i* of the type *k* in region *r* in year *t*. The risk-adjustment procedure described above ensures that we have already taken into account the demographic and clinical factors driving differences in cesarean rates among hospitals. On the other hand, the first group of explanatory variables *Dem* aims at controlling for potential differences in preferences among patients (not driven by risk factors but) more driven by socio-economic factors. In particular, among the demand factors we have: female employment rate *FER* at the province level, usually considered the catchment area for hospitals providing childbirth services; regional capital dummy, meaning that *RC* = 1 if the hospital *i* is located in a province which is the regional capital; province capital dummy, meaning that *PC* = 1 if the hospital *i* is located in a municipality which is the province capital. Then, we control for supply factors potentially affecting cesarean rates, namely, *Bed* is the total number of beds and *Birth* is the total number of childbirth deliveries in hospital $i$ in year $t$, capturing the size and the level of specialization of hospitals[11]. Considering the previous evidence on the relevance of *learning-by-doing* effects in the provision of health care services (e.g., Birkmeyer et al., 2002; Chandra et al., 2011), these supply factors might be important in explaining the shares of cesarean sections.

The explanatory variable *FEEDIFF* is our DRG tariff differential indicator, as described in the previous section: the tariff differential between cesarean and vaginal deliveries with complication and comorbidities. The variable *FEEDIFF* only considers the variability of DRG tariffs among Italian regions, aiming to capture the relative financial convenience to execute cesarean sections in each region. Unfortunately, data availability prevents us from considering also the variability of DRG tariffs among different hospitals within the same region; therefore, the magnitude of the impact of *FEEDIFF* on hospital caesarean rates could be in theory under-estimated.

The variable $\frac{\sum_{j \in r, j \neq i} RACR_{jrkt}}{n_r - 1}$ represents the main variable of interest in our paper. As can be easily seen, it is the average risk-adjusted cesarean rate of all hospitals belonging to the same institutional authority $r$, excluding hospital $i$. Therefore, it can be considered the average (inappropriate) behavior of hospital $i$' peers; consequently, the coefficient $\rho$ can be interpreted as the peer effect in the inappropriate behavior among hospitals.

Finally, we include in the estimation a large set of hospital ($\theta$) regional ($\varphi$) and time ($\mu$) fixed effects, aiming at capturing those unobservable differences among hospitals, regions and years which could affect cesarean section rates. Indeed, this large set of fixed effects should help us to alleviate omitted variables bias as well as model misspecification.

As long as exogeneity $E(\varepsilon_{irkt} | X_{irkt},) = 0$ holds, we might interpret the estimated coefficients as consistent. In the equation (17), we are particularly interested in estimating $\rho$, from which [exp($\rho$) – 1]*100 can be interpreted as the percentage change in the odds ratio of the share of cesarean sections due to a marginal increase in the average cesarean rate of the reference peers. As far as the identification of $\rho$ is concerned, this is a particularly fortune case of peer effects analysis, since our non-linear model does not suffer for the "reflection

[11] In the first version of this paper we considered also some other demand and supply factors potentially affecting cesarean sections, as local female tertiary education rate, local household income, number of personnel units. Not surprisingly, all these variables turn out to be highly correlated with the others already considered, inducing a multicollinearity problem in our estimates. Therefore, we removed them from the estimates, knowing that we are already controlling for the underlying factors potentially driving differences among cesarean section rates.

problem" of the linear-in-mean models. In fact, the non linearity in our model (17) breaks the linear dependence between the outcome variable $RACR_{irkt}$ and the endogenous effect $\frac{\sum_{j\in r,j\neq i} RACR_{jrkt}}{n_r - 1}$, which is the basis of Maski's (1993) result of nonidentification in the linear case. Moreover, the use of panel data in (17) allows us to address consistently group level unobservables $\varphi$ potentially correlated with the endogenous effect, which represents a potential source of nonidentification even in the non-linear model[12]. In particular, Brock and Durlauf (2007, Proposition 7, p. 67) provide the formal result of identification in non-linear models with panel data[13].

As the number of cross-sectional observations is larger than the number of time-series ones, heteroscedasticity could be a potential problem in our estimates. In particular, the share of cesarean sections might exhibit a different variability according to both hospital size and specialization, eventually implying heteroscedastic residuals. Furthermore, the variability of cesarean rates might not be constant among regions and hospital types. Therefore, for all our estimates, we provide standard errors that are robust to the presence of heteroscedasticity.

### 4.2 Spatial econometric model

An alternative empirical approach to study the presence of social interactions among agents is the more recent (but, certainly, less microfounded) spatial econometric. By now, several papers in the literature have performed spatial analysis to infer similar effects in agents' behavior (e.g., Moscone et al., 2012; Gravelle et al., 2013; Atella et al., 2014). Indeed, the interesting empirical implication of our model is that cesarean section rates should be spatially correlated according to the sharing of the same institutional authority. Therefore, as a further evidence of the significant presence of peer effects among hospitals, we carry out also the following spatial econometric analysis, exploiting the panel dimension of our data.

Looking at the specific model, when spatially lagged dependent variable, regressors and error term are included simultaneously, the model is not identified unless at least one of these interaction effects is excluded (e.g., Maski, 1993). As suggested by LeSage and Pace (2009), the choice of the excluded effect should be driven by the specific research question under

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[12] In this regard, the identification of endogenous effects in non-linear models with group level unobservables would require specific restrictions on the joint distribution of observables and unobservables, likely not reasonable in many contexts under analysis (see e.g., Brock and Durlauf, 2007).

[13] Notice that Brock and Durlauf (2007, Proposition 7, p. 67) provide the formal result of partial (not full) identification in non-linear models with group level unobservables, meaning that not all parameters can be identified. However, the unique parameter not being identified is that relating to the time invariant group-specific characteristics; indeed, this is not surprising because there is no way to distinguish between the time invariant group-specific characteristics and group level unobservables. Looking at our model (17), however, we do not have any time invariant group specific characteristics, but only time variant group specific characteristics which are fully identified, along with the endogenous effect $\rho$.

analysis. According to our model in section 2, hospitals' behavior within the same region should not be affected by their peers' characteristics, rather by their peers' behavior. Specifically, hospital $i$'s caesarean section rate (13) is not affected by his peers' supply factors, rather by his peers' caesarean section rates. Therefore, we specify the following spatial autoregressive model with autoregressive disturbances (SAC), provided that we perform standard model selection tests:

$$RACR_{irkt} = \beta * X_{irkt} + \delta * FEEDIFF_{rt} + \rho \sum_j w_{ij} RACR_{irktj} + \theta_k + \varphi_r + \mu_t + \varepsilon_{irkt} \quad (18)$$

$$\varepsilon_{irkt} = \phi \sum_j m_{ij} \varepsilon_{irktj} + v_{irkt} \quad (19)$$

where $X_{irkt}$ is the vector of demand and supply factors, $w_{ij}$ and $m_{ij}$ are the $(i,j)$ elements for each $t$ of the spatial matrixes $\boldsymbol{W}$ and $\boldsymbol{M}$ respectively[14].

Differently from the standard spatial analysis, however, the spatial weights matrix is not based on the geographic distance among hospitals; rather, it is based again on the sharing of the same institutional authorities, coherently with our model of hospitals' behavior. More specifically, the row-standardized spatial weights matrixes $\boldsymbol{W} = \boldsymbol{M}$ are as follows:

$$w_{ij} = m_{ij} = \begin{cases} 0 & if\ i = j \\ \frac{1}{n_r - 1} & if\ r_i = r_j \\ 0 & if\ r_i \neq r_j \end{cases} \quad (20)$$

implying that each hospital is correlated only with the other hospitals within the same region. Therefore, the spatial weights matrix (20) emphasizes the primary role of institutions respect to geography in affecting agents' behavior (e.g., Rodrik et al., 2004; Arbia et al., 2009; Atella et al., 2014). In particular, this reflects our interpretation of peers effect among hospitals as a *constraint interaction* within the same institutional authority.

[14] According to the spatial econometric literature (e.g., Anselin, 1988), the two spatial matrixes ***W*** and ***M*** (respectively, for the dependent variable and disturbances) can be different; however, in the following spatial analysis we consider ***W*** = ***M***.

## 5. Results

In this section we present the results of the empirical analysis, following the same structure of the previous section. First, we show the estimates for the LOGIT model, along with the generalized linear model (GLM), potentially an econometric specification even more appropriate for cesarean section rates. Then, we move to spatial analysis, where we present the estimates for different spatial econometrics models, along with standard model selection tests. Finally, we conduct sensitivity analyses to check the robustness of our findings.

### 5.1 LOGIT model

In Table 2 we report the estimates from the LOGIT model (17). As discussed above, heteroscedasticity may be present in our estimates; therefore, we use a Generalized Least Squares (GLS) estimator for panel data[15]. As can be seen in column (1), the point estimate of our main variable of interest *Peers RACR* is positive and strongly significant. In particular, the coefficient of 0.027 implies a marginal effect of 0.006, meaning that an increase of one percentage point in peers' cesarean rates would imply an increase of about 0.6 percentage points in hospitals' cesarean rate[16]. Therefore, our estimate of *Peers RACR* seems to suggest a significant presence of peer effects among Italian hospitals.

Looking at the demand and supply factors, while the female employment rate at the province level (*FER*) does not seem to play a significant role[17], both regional (*RC*) and province capital (*PC*) dummies turn out to be positive and significant at 1%, implying that on average patients in big provinces and big cities tend to prefer more cesarean section than vaginal deliveries, *ceteris paribus*. Among the supply factors, the number of childbirth deliveries (*Birth*) turns out to be significant, while the hospital size (*Bed*) does not seem to play any role, probably because we control for hospital type. In particular, the negative coefficient of *Birth* indicates that more specialized hospitals tend to exhibit lower cesarean rates, suggesting the presence of a *learning-by-doing* effect in the provision of childbirth delivery services.

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[15] We also tried to run a pooled OLS (POLS) estimator with robust standard errors (POLS results available upon request), obtaining coefficients fairly close to GLS in Table 2 but, not surprisingly, estimates were less precise.

[16] In particular, we are considering the standard marginal effect at means (MEMs), that is

$$\frac{\partial RACR}{\partial Peers\ RACR} = \delta\left(F(\overline{\boldsymbol{X}}\boldsymbol{\beta}) - F(\overline{\boldsymbol{X}}\boldsymbol{\beta})^2\right) = \delta\ \frac{e^{(\overline{X}\beta)}}{\left(1 + e^{(\overline{X}\beta)}\right)^2}$$

[17] We find similar results if we include local female tertiary education rate or local household income, instead of female employment rate; indeed, this is not surprising as all these demand factors tend to be positively correlated in our sample.

**Table 2 – Risk-Adjusted Cesarean Rates for First-Time Mothers (LOGIT Model)**

| | (1) | (2) |
|---|---|---|
| | LOGIT[a] | GLM[b] |
| *Peers RACR* | 0.027<br>(0.002)*** | 0.025<br>(0.002)*** |
| *FER* | -0.003<br>(0.002) | -0.003<br>(0.002) |
| *RC* | 0.074<br>(0.020)*** | 0.111<br>(0.022)*** |
| *PC* | 0.085<br>(0.022)*** | 0.081<br>(0.023)*** |
| *Bed* | 0.000<br>(0.000) | 0.000<br>(0.000) |
| *Birth* | -0.001<br>(0.000)*** | -0.001<br>(0.000)*** |
| *FEEDIFF* | 0.279<br>(0.089)*** | 0.226<br>(0.086)*** |
| *Hospital Unit* | -0.061<br>(0.036)* | -0.098<br>(0.039)** |
| *Private Hospital* | 0.626<br>(0.038)*** | 0.632<br>(0.037)*** |
| *Costant* | -1.883<br>(0.162)*** | -1.670<br>(0.181)*** |
| Hospital type dummies | YES | YES |
| Regional dummies | YES | YES |
| Year dummies | YES | YES |
| Observations | 2952 | 2952 |

LOGIT: logit model; GLM: generalized linear model for fractional regression; FER: female employment rate; RC: regional capital; PC: province capital; FEEDIFF: index of fee differential (differential between cesarean and vaginal DRG tariffs W CC);
[a] GLS estimator for panel data. [b] Generalized linear estimator for fractional variable by Papke and Wooldridge (1996).
Robust standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

As far as the financial factor is concerned, the point estimate of *FEEDIFF* is positive and significant at 1%, implying that higher DRG tariff differentials are associated with higher cesarean rates. In particular, the coefficient of 0.279 implies a marginal effect of 0.058, meaning that a marginal increase of *FEEDIFF* would imply an increase of 5.8 percentage points in the probability of a cesarean deliveries. Indeed, this might suggest that in those regions where the financial incentives to execute cesarean sections are relatively higher, providers respond in a strategic way, by shifting procedures towards more cesarean deliveries.

Finally, interesting regularities in the differences among hospital types clearly emerge in our estimates. In particular, directly managed public hospitals (*Hospital Units*), where financial factors should not play a big role, tend to experience lower cesarean rates; conversely, accredited private hospitals (*Private Hospitals*), where financial aspects should be crucial, tend to execute significantly more cesarean sections, *ceteris paribus*. Therefore, such differences among hospital types seems also to suggest that providers behave strategically in accordance to financial incentives.

From an econometric point of view, though the LOGIT model (17) is certainly more appropriate than the simple linear probability model, it might not be the most appropriate for cesarean section rates. In this regard, Papke and Wooldridge (1996) noted that the log-odds type procedures implicitly assume a standard normal distribution for the error term, which might not be appropriate for regression models with fractional dependent variable. Therefore, since fractional variables are the result of a dichotomous process, they proposed a more attractive quasi-likelihood estimation method in the framework of generalized linear models (GLM), using the LOGIT transformation as link function but assuming a binomial distribution for the error term[18]. To the extent that the share of cesarean sections is the result of the dichotomous choice vaginal/cesarean deliveries, the use of a GLM with LOGIT link function and binomial distribution could result even more appropriate.

Therefore, in the second column of Table 2, we run the same model but for the described GLM estimator. As can be seen from column (2), however, all the results from the LOGIT model are also confirmed by the GLM estimates. In particular, the coefficient of *Peers RACR* is still positive and strongly significant, implying a marginal effect of about 0.5 percentage points in hospitals' cesarean rate. Similarly, all other results concerning the role of demand, supply and financial factors are also full in line with the LOGIT estimates.

Overall, both the LOGIT and GLM estimates apparently support all the predictions coming from our theoretical model of hospital behavior. Provided that in (17) we control for

[18] Indeed, Papke and Wooldridge (1996) proposed the so-called "fractional logit" in the cross-section context. However, there are no serious drawbacks in applying their GLM approach with panel data, provided that one "... can account for unobserved heterogeneity that is possibly correlated with the explanatory variables ..." (Papke and Wooldridge, 2008). In this regard, we are confident that in our study the large structure of fixed effects should be sufficiently able to account for the unobserved heterogeneity, without suffering from the incidental parameters problem. For a study applying the "fractional logit" with panel data see e.g. Hausman and Leonard (1997), where they use a similar strategy to account for the unobserved heterogeneity.

demand, supply and financial factors, we interpret our estimate as the (reduced form) hospitals' reaction function (13) to the inappropriate behavior of their peers within the same RHA. Therefore, our estimate of *Peers RACR* suggests a significant presence of peer effects among (the inappropriate behavior of) hospitals. In particular, our estimate implies that an increase of one percentage point in peers' cesarean rates leads to an increase of about 0.6 percentage points in hospitals' cesarean rate.

Following the classification proposed by Manski (2000), we interpret this evidence as a large presence of *constraint interactions* in the healthcare sector, intending that the behavior of peers represents a constraint for the inappropriate behavior of hospitals within the same institutional authority. Looking at our theoretical model of hospitals' behavior, indeed, this interpretation would seem fairly reasonable for the specific context of the healthcare sector.

### 5.2 Spatial econometric model

We now move to the spatial analysis. Since the implication of our theoretical model is that cesarean rates should be spatially correlated within the same institutional authority, the following spatial analysis could provide further support to our model and, in turn, provide evidence of the presence of peer effects among hospitals. As we said above, several papers have recently performed spatial analysis to infer similar effects in agents' behavior (e.g., Moscone et al., 2012; Gravelle et al., 2013; Atella et al., 2014).

We start our analysis by testing pre-emptively whether cesarean section rates show spatial dependence within the same RHA. In particular, in Table 3 we show the results of the Moran's tests, using (20) as the spatial weights matrix. As can be seen, we find evidence of spatial dependence among cesarean section rates, regardless we compute the Moran's test to the whole panel or to each year one by one in our dataset.

**Table 3 – Moran's I Test**

| Test | I Statistics | p-value |
|---|---|---|
| Moran's $I_{Panel}$ | 0.473 | 0.000 |
| Moran's $I_{2007}$ | 0.473 | 0.000 |
| Moran's $I_{2008}$ | 0.451 | 0.000 |
| Moran's $I_{2009}$ | 0.451 | 0.000 |
| Moran's $I_{2010}$ | 0.440 | 0.000 |
| Moran's $I_{2011}$ | 0.498 | 0.000 |
| Moran's $I_{2012}$ | 0.508 | 0.000 |

**Table 4 – Risk-Adjusted Cesarean Rates for First-Time Mothers (Spatial Model)**

| | (1) | (2) | (3) |
|---|---|---|---|
| | SAC | SAR | DURBIN |
| *FER* | -0.001<br>(0.001) | -0.001<br>(0.001) | -0.001<br>(0.001) |
| *RC* | 0.027<br>(0.005)*** | 0.027<br>(0.005)*** | 0.029<br>(0.005)*** |
| *PC* | 0.014<br>(0.005)*** | 0.013<br>(0.005)*** | 0.014<br>(0.005)*** |
| *Bed* | 0.000<br>(0.000) | 0.000<br>(0.000) | 0.000<br>(0.000) |
| *Birth* | -0.001<br>(0.000)*** | -0.001<br>(0.000)*** | -0.001<br>(0.000)*** |
| *FEEDIFF* | 0.031<br>(0.018)* | 0.033<br>(0.019)* | 0.031<br>(0.019)* |
| *Hospital Unit* | -0.017<br>(0.008)** | -0.015<br>(0.008)* | -0.016<br>(0.008)** |
| *Private Hospital* | 0.152<br>(0.007)*** | 0.153<br>(0.007)*** | 0.151<br>(0.007)*** |
| *RHO* | 0.430<br>(0.058)*** | 0.396<br>(0.034)*** | 0.394<br>(0.034)*** |
| *Bed* | | | 0.000<br>(0.000) |
| *Birth* | | | 0.000<br>(0.000) |
| *LAMBDA* | -0.082<br>(0.126) | | |
| LR Test (SAC vs. SAR) | | p-value = 0.511 | |
| LR Test (Durbin vs. SAR) | | p-value = 0.999 | |
| AIC | -4589.063 | -4590.632 | -4577.962 |
| BIC | -4487.229 | -4494.788 | -4476.128 |
| Hospital type dummies | YES | YES | YES |
| Regional dummies | YES | YES | YES |
| Year dummies | YES | YES | YES |
| Observations | 2952 | 2952 | 2952 |

DURBIN: spatial durbin model; SAR: spatial autoregressive model; SAC: spatial autoregressive model with autoregressive disturbances; FER: female employment rate; RC: regional capital; PC: province capital;
Clustered standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Moving from the simple Moran's test, in Table 4 we show the results of different spatial econometric models. In regard to the model selection, as we argued above, hospitals' behavior should not be affected by their peers' characteristics, rather by their peers' behavior. Accordingly, we estimate first a spatial autoregressive model with autoregressive disturbances (SAC), as specified in (18) and (19). As can be seen, the spatial effect in the dependent variable (*RHO*) is positive and strongly significant, whereas the spatial effect in the error term (*LAMBDA*) turns out to be not significant. To this extent, we estimate a spatial autoregressive model (SAR) excluding the autoregressive disturbances and, then, we compute standard model selection tests. For the sake of completeness, we estimate also a spatial Durbin model including supply factors as spatially regressors. Indeed, both the *LR* tests and the two standard information criteria Akaike (*AIC*) and Bayesian (*BIC*), give a clear preference for the SAR; therefore, we consider the SAR as the preferred model in our spatial analysis.

As Table 4 clearly shows, the empirical results support the prediction of our theoretical model. In particular, the spatial coefficient *RHO* in the dependent variable is positive and strongly significant, implying that there is a dependence among hospitals' behavior within the same RHA. On the other hand, hospital cesarean rates do not seem to have any relation with their peers' characteristics, as our model predicts. Looking at the magnitude of our estimated spatial effect, we find that *RHO* is equal to 0.396, a value in line with few previous studies estimating spatial correlation among health providers' behavior within the same institutional authority (e.g., Atella et al., 2014). Focusing on the other factors, we find empirical results similar to the LOGIT model for demand, supply and financial factors, as well as the differences among hospital types.

Therefore, our spatial analysis apparently confirms the prediction of our model on the spatial correlation among hospital cesarean rates within the same RHA. Although the spatial econometric models are less microfounded than the LOGIT model (17), the evidence coming from the estimates in Table 4 should provide further support to our theoretical model and, in particular, provide further evidence of the significant presence of peer effects among hospitals sharing the same institutional authority.

**5.3 Sensitive analysis**

In this last section we provide some sensitivity analysis to test further the robustness of our empirical results. Firstly, to test whether our findings depend significantly on our sample, we re-estimate all three models (LOGIT, GLM, SAR) excluding all regions one-by-one. To some extent, this robustness check seems especially required for the Italian case, given the already mentioned differences among the Italian regions. Moreover, in line with the actual distribution of Italian hospitals, the number of units in our sample is not homogeneous among regions, implying that each region might have a different weight in determining the results.

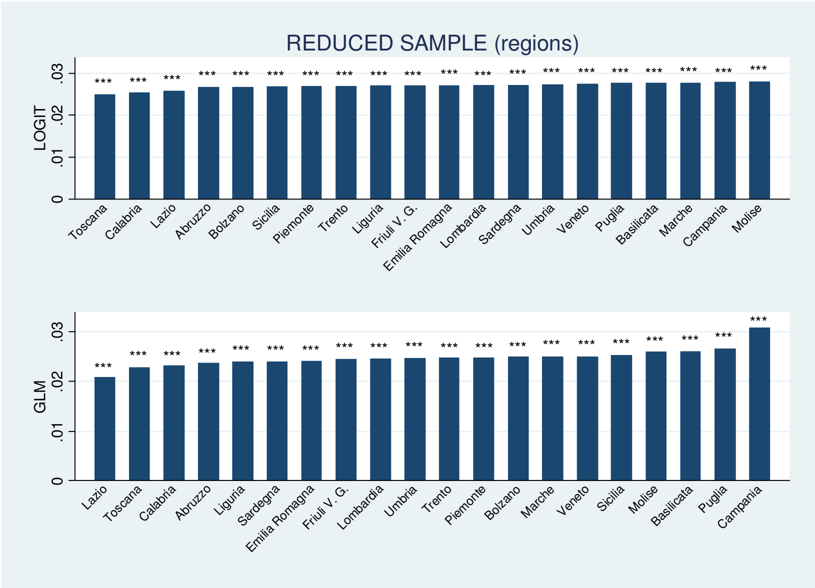


**Figure 7.** ***Peers RACR*** **from the reduced sample (regions)**

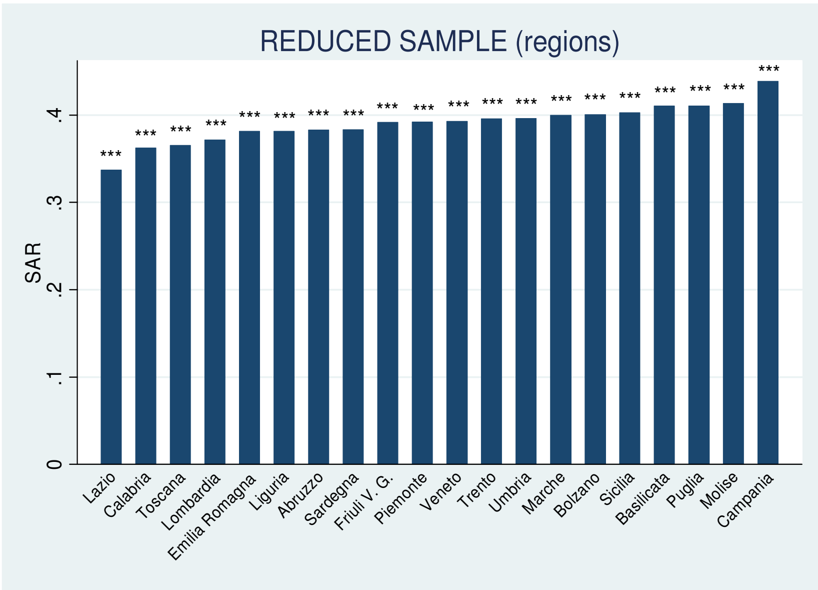


**Figure 8.** ***RHO*** **from the reduced sample (regions)**

In Figure 7 we show the coefficients of *Peers RACR* for the LOGIT and GLM models, arranged from the smallest to the greatest; similarly, in Figure 8 we show the spatial coefficient *RHO* for the SAR model. As the figures show, however, the estimates from the reduced sample do not change our conclusion on the presence of peer effects among hospitals.

Then, we compute the same exercise for the time dimension in our sample, meaning that we re-estimate all three models excluding all years one-by-one. Again, the estimates confirm our results on peer effects, as clearly shown in Figure 9 and Figure 10.

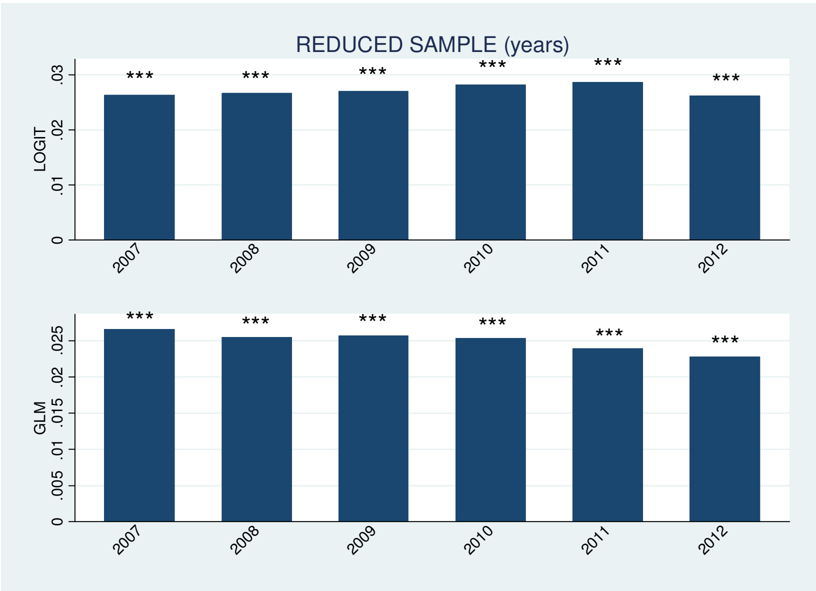


**Figure 9.** ***Peers RACR*** **from the reduced sample (years)**

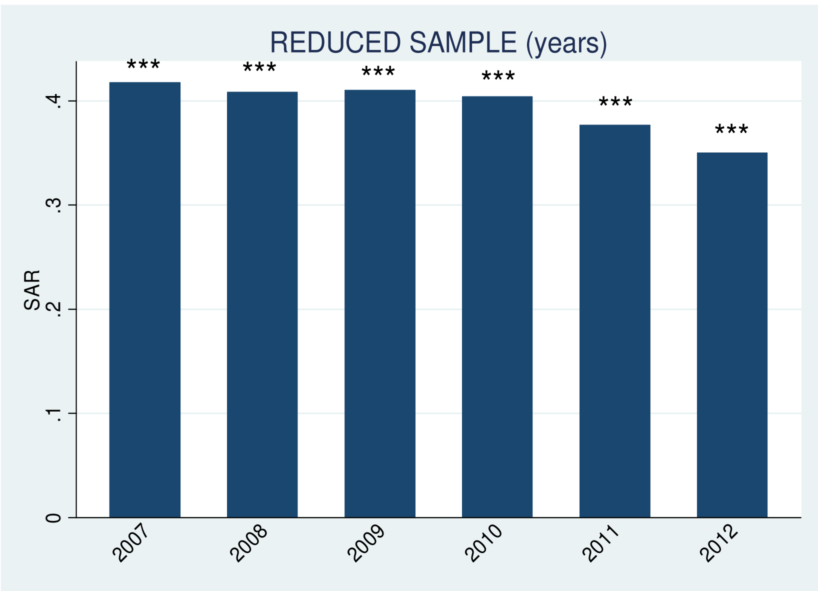


**Figure 10.** ***RHO*** **from the reduced sample (years)**

**Table 5 – Risk-Adjusted Cesarean Rates for First-Time Mothers (Lagged *Peers RACR*)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | LOGIT[a] | LOGIT[a] | GLM[b] | GLM[b] |
| *Peers RACR* | | 0.025<br>(0.002)*** | | 0.028<br>(0.006)*** |
| *Peers* $RACR_{t-1}$ | 0.013<br>(0.002)*** | 0.002<br>(0.002) | 0.025<br>(0.002)*** | -0.002<br>(0.006) |
| *FER* | -0.006<br>(0.002)*** | -0.001<br>(0.002) | -0.002<br>(0.002) | -0.002<br>(0.002) |
| *RC* | 0.120<br>(0.021)*** | 0.080<br>(0.021)*** | 0.113<br>(0.024)*** | 0.107<br>(0.024)*** |
| *PC* | 0.091<br>(0.022)*** | 0.070<br>(0.023)*** | 0.073<br>(0.025)*** | 0.074<br>(0.025)*** |
| *Bed* | 0.000<br>(0.000) | 0.000<br>(0.000) | 0.000<br>(0.000) | 0.000<br>(0.000) |
| *Birth* | -0.001<br>(0.000)*** | -0.001<br>(0.000)*** | -0.001<br>(0.000)*** | -0.001<br>(0.000)*** |
| *FEEDIFF* | 0.243<br>(0.092)*** | 0.281<br>(0.090)*** | 0.157<br>(0.094)* | 0.215<br>(0.093)*** |
| *Hospital Unit* | -0.068<br>(0.037)* | -0.070<br>(0.037)* | -0.105<br>(0.042)** | -0.098<br>(0.042)** |
| *Private Hospital* | 0.603<br>(0.038)*** | 0.589<br>(0.038)*** | 0.623<br>(0.041)*** | 0.615<br>(0.040)*** |
| *Costant* | -1.253<br>(0.169)*** | -1.970<br>(0.173)*** | -1.700<br>(0.200)*** | -1.767<br>(0.198)*** |
| Hospital type dummies | YES | YES | YES | YES |
| Regional dummies | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES |
| Observations | 2460 | 2460 | 2460 | 2460 |

LOGIT: logit model; GLM: generalized linear model for fractional regression; FER: female employment rate; RC: regional capital; PC: province capital; FEEDIFF: index of fee differential (differential between cesarean and vaginal DRG tariffs W CC);
[a] GLS estimator for panel data. [b] Generalized linear estimator for fractional variable by Papke and Wooldridge (1996).
Robust standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Since agents might infer their peers' behavior from the previous cesarean section rates, finally, we re-estimate the LOGIT model (17) considering the lagged (instead of the contemporaneous) *Peers RACR*[19]. As Table 5 shows, if we include the lagged *Peers RACR* in place of the contemporaneous variable, then the estimated coefficient is positive and strongly significant. Once we include both the lagged and contemporaneous *Peers RACR*, however, only the contemporaneous variable is significant, whereas the lagged *Peers RACR* turns out to be not significant. To this extent, the estimates in Table 5 seems to support our use of the contemporaneous *Peers RACR* throughout the paper. And, indeed, the significant role of contemporaneous cesarean section rates in our estimates appears to be more in line with our interpretation of the peer effects among hospitals as *constraint interaction*, emerging from the enforcement congestion within the same RHA.

Overall, our empirical findings appear to be fairly robust and rather stable to the sample used in the analysis. Provided that we control for demographic and risk factors, demand, supply and financial factors, as well as several unobserved fixed-effects, we interpret our estimates as fairly consistent and, in particular, the estimated *Peers RACR* as the peer effects in the inappropriate behavior among hospitals within the same RHA.

## 6. Conclusion

In this paper we study the presence of social interaction effects in the inappropriate behavior among hospitals. In particular, we develop a theoretical model of hospitals' behavior where the effect of peers' behavior emerges by the simple sharing of the same institutional authority. The main intuition of our theoretical prediction is that each institutional authority cannot afford to contrast the inappropriate behavior of all hospitals under its authority; therefore, the peers' inappropriate behavior can reduce the hospital's probability of being audited and, in turn, increase the expected value of inappropriate claims. In other words, higher hospitals' inappropriate behavior can produce an enforcement congestion effect which makes the open road to the inappropriate behavior of their peers.

Subsequently, we test the implications of our model and, in particular, the presence of peer effects in the Italian hospital sector, controlling for demand, supply and financial factors. Indeed, the Italian NHS is an especially interesting case for testing such hypothesis, as

[19] The use of lagged peers' variable has been often used, for instance, to study the presence of peer effects in the performance of students at school or college. However, in the education literature the use of peers' lagged performance has mainly represented a way to get identification of peer effects in linear-in-mean models (see e.g., Mansky, 1993, 2000). Differently, in our non-linear-in-mean model the identification of peer effects does not require necessarily the use of lagged peers' variable (e.g., Brock and Durlauf, 2007), as discussed in the previous section. Therefore, in our paper the use of lagged peers' variable represents just a robustness check of our empirical results.

decentralization processes have made the RHAs the main institutional authorities for each hospital and, furthermore, the reference third-party payers for the health services provided. Specifically, we perform first a more traditional peer effects estimate, really close to our microfounded model of hospital's behavior; then, we carry out also the more recent (but, certainly, less microfounded) spatial econometric analysis, where we emphasize more the role of institutions respect to geography. Among the other factors, both estimates show a significant and strong presence of peer effects among hospitals, robust to sensitivity analyses. Following the classification proposed by Manski (2000), we interpret this evidence as a large presence of *constraint interactions* in the healthcare sector, intending that the behavior of peers represents a constraint for the inappropriate behavior of hospitals within the same institutional authority.

The results of this paper have important implications for the healthcare policy. The first immediate implication is that health authorities can reduce inappropriate behaviors at a cost smaller than that of auditing all hospitals under their authority. Through the social interaction effect, in fact, a small increase in audit activity would generate a reduction in hospitals' inappropriate behavior larger than the effect induced by the increase in the general audit probability. More importantly, the significant presence of *constraint interactions* among hospitals implies that, if it is true that the inappropriate behavior of hospitals frustrates the activity of health authorities, on the other hand, the appropriate behavior of other hospitals contributes to the purpose of reducing the inappropriateness in the system. To this extent, the resource allocation among local authorities should not be a stable process, as usually it is, but should internalize the congestion externality, especially when different levels of inappropriate behavior are observed among local authorities as in the Italian NHS. Moreover, a more flexible resource allocation among local authorities might counteract the decrease in the perceived probability of being audited when higher peers' inappropriate behavior is observed and, in turn, prevent hospitals to increase inappropriate claims. Therefore, our paper suggests that a more flexible allocation of even the same resources among local authorities, ideally internalizing the congestion externality among hospitals, has the potential to reduce the inappropriateness of the healthcare system without increasing the operating costs.

Finally, we emphasize that our study focuses more on the inappropriateness, a concept more related to the efficiency of health expenditure. However, the excess of cesarean sections showed in our study not only implies higher healthcare costs, but also might lead to negative health outcomes in both mothers and newborns. Therefore, future research should question whether the excess of cesarean sections might have also negative effects on patient outcomes.

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