IMITATIVE PRICING: THE IMPORTANCE OF NEIGHBORHOOD EFFECTS IN PHYSICIANS' CONSULTATION PRICES

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Benjamin Montmartin
Marcos Herrera-Gomez

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Imitative pricing: the importance of neighborhood effects in physicians' consultation prices

Benjamin Montmartin[*], Marcos Herrera-Gomez[†]

Abstract

During the last 30 years in France, concerns about healthcare access have grown as physician fees have increased threefold. In this paper, we developed an innovative structural framework to provide new insights into free-billing physician pricing behavior. We test our theoretical framework using a unique geolocalized database covering more than 4,000 private practitioners in three specializations (ophthalmology, gynecology and pediatrics). Our main findings highlight a low price competition environment driven by local imitative pricing between physicians, which increases with competition density. This evidence in the context of growing spatial concentration and an increasing share of free-billing physicians calls for new policies to limit additional fees.

JEL Classification: H51, C21, I11, I18

Keywords: Imitative pricing, Health care access, Local competition, Spatial effects.

[*]Corresponding author; SKEMA Business School, Université Côte d'Azur (GREDEG), OFCE SciencesPo, email: benjamin.montmartin@skema.edu.

[†]CONICET - IELDE, National University of Salta; Av. Bolivia 5150 (A4408FVY), Salta, Argentina; email: mherreragomez@conicet.gov.ar.

1 Introduction

The growing medical desertification in most OECD countries driven by an increasing spatial concentration of physicians (Pál et al., 2021) is a huge concern for policy-makers, as it reduces healthcare access and increases inequalities. OECD (2016) mentioned that "The uneven geographic distribution of doctors is one of the most common health workforce policy challenges OECD countries currently face." If medical desertification is an important driver of unequal access to healthcare services, another reality that has received less attention from economists so far (see Gaynor and Town, 2012) could become a major concern for policy-makers: the pricing of physician services. Indeed, some OECD countries[1] allow some or all of their physicians to set their prices freely, with the result that pricing of physician services impacts access to healthcare.

France is an interesting context in which to explore physicians' pricing decisions. Approximately 40% of physicians (CNAMTS, 2017), mainly specialists, are able to balance bill their patients based on no other limit than their evaluation of "tact and moderation". The part of the bill that is above the regulated fee is not covered by National Health Insurance (NHI).[2]

As physicians in France are free to choose their location, the geographical concentration of free-billing physicians is another concern for healthcare access. Indeed, there is a well-known risk that free-billing physicians locate in similar attractive locations characterized by excess demand at regulated prices, high income and amenities. The study on the location of liberal health professionals in France proposed by Barlet and Collin (2009) tends to support this idea. Indeed, by comparing the adequacy of the different professions to the location of the French population, they show that even if general practitioners (GP) are uniformly spread over the French territory, this is not the case for physician specialists such as gynecologists, pediatricians or ophthalmologists. Their Gini index is nearly four times higher than that of GPs. This risk was discussed many years ago by Feldman and Sloan (1988), claiming that it is not higher density that causes higher fees but rather the high level of fees in an area that attracts more doctors.

The objective of this paper is to provide new evidence of free-billing physicians' pricing behavior using a structural approach to provide reliable results. This is an important and necessary step to better understand which kind of policy tools could limit additional fees and guarantee access to healthcare. In achieving this objective, we make several contributions to the existing literature. First, we propose a closed-form solution of a circular city model with heterogeneous physicians where consultation quality influences both patients' utility and physicians' costs. This allows us to highlight how individual and neighbor quality influence equilibrium prices. We are also able to provide new insights concerning the effects of competition intensity on prices. Second, we build a unique geolocalized database of more than 4,000 private practitioners of three specializations

[1] Namely Australia, Austria, Belgium, France and New Zealand (see Kumar et al., 2014). We exclude countries such as Greece or Hungary where physicians are not allowed to charge additional fees in principle, but where informal payments are common practice. We also exclude countries such as Finland, Ireland, Mexico and the UK, where physicians are free to charge any price for private services paid on a fee-for-service basis. This is because in those countries, the main mode of payment of general practitioners and specialist physicians is not fee-for-services but a salary. Consequently, this issue affects a very small proportion of physicians.

[2] They may be reimbursable from optional private insurance depending on the type of coverage chosen.

(ophthalmology, gynecology and pediatrics) that allows us to estimate the structural equilibrium price model using spatial econometric techniques. We construct specific competition areas as well as specific competition measures for each physician that are not restricted by administrative boundaries or arbitrary thresholds. Third, contrary to the existing health economics literature using spatial econometric methods, we use a two-step procedure controlling for sample selection bias, unknown heteroskedasticity and unknown distribution of errors using the generalized method of moment (GMM) estimator instead of the maximum likelihood (ML) estimator. Then, our final contribution is to provide robust evidence on the pricing behavior of physicians. We find a significant positive spatial dependence among neighboring physicians' prices for all specializations, indicating that prices are strategic complements. Our theoretical model suggests that consultation quality reduces price competition in the French context. The spatial dependence in price is estimated to be between 0.3 and 0.4, showing important local imitative pricing. Concerning the effect of competition, we obtain evidence that free-billing physicians (especially gynecologists and ophthalmologists) adopt noncompetitive behaviors, implying that greater density is associated with higher prices and stronger imitative pricing. This last result is also explained by the existence of a substitution effect between vertical and horizontal differentiation. We believe our results provide new insights into the significant price differences in French cities and discuss the best tools for limiting additional fees.

The rest of the paper is organized as follows. In Section 2, we perform a literature review on the pricing conduct of physicians. Section 3 develops the circular city model with heterogeneous free-billing physicians. In Section 4, we discuss the French primary care system, detail the construction of our database and introduce descriptive statistics. Section 5 presents the structural spatial econometric models tested and our identification strategy. Section 6 provides our empirical results and some policy discussions. Conclusions and future research avenues are presented in Section 7.

2 Literature review: Pricing conduct of physicians

Economists have identified and discussed various determinants of physicians' fees from individual characteristics (such as gender) to market organization. Among them, one of the topics that received the greatest interest is the relationship between price and competition intensity, partly because the evidence is still contradictory. Indeed, some recent empirical results are in line with the standard theory prediction, i.e., that fees decrease if local competition increases; see Johar (2012) and Gravelle et al. (2016) for Australia and Choné et al. (2019) for France. However, many other empirical studies find exactly the opposite result; see Richardson et al. (2006) for Australia, Bellamy and Samson (2011) for France or Fuchs (1978) and Pauly and Satterthwaite (1981) for the US. Several theoretical frameworks have been proposed to explain this apparent paradox.

2.1 Information asymmetries as sources of market power

One of the most controversial arguments justifying this paradox is the notion of physician-induced demand (PID). Rice (1983) defines PID as "demand inducement [occurring] when a physician recommends or provides services that differ from what the patient would choose if he or she had available the same information and knowledge as the physician" (p. 803). This effect implies that physicians can shift the consumer demand curve in their own interest to increase quantity and/or price. Consequently, PID could explain why a higher density of physicians is not associated with a lower average fee, and much empirical evidence has been proposed (see Evans (1974), Fuchs (1978), Rice (1983), Wedig et al. (1989), Rizzo and Blumenthal (1996), Delattre and Dormont (2003) and Coudin et al. (2015)). Although the PID argument has been strongly criticized for its weakness of theoretical and empirical works (see Stano, 1985, for example), more recent studies still highlight the existence of inducement elements in physicians pricing decisions (see Rochaix and Jacobzone, 1997; Johnson, 2014; Coudin et al., 2015). Consequently, as stated by Johnson (2014), the question is no longer to debate the existence of PID but rather to evaluate its economic importance. This is still an open research question even if it seems that PID effects on physician prices are less important than initially viewed by PID defenders (Stano, 1987) given the number of other determinants.

The notion of PID is directly related to target income theory (Newhouse, 1970; Evans, 1974; Wedig et al., 1989; Rizzo and Blumenthal, 1996). The main assumption behind this theory is that physicians aim at a predefined level of income. When the number of physicians increases, the demand for each physician decreases; thus, to reach their target income, physicians have to set higher fees or increase their output. The underlying hypothesis is that physicians have monopoly power, largely explained by the existence of PIDs. However, the target income hypothesis has been rejected by several economists (Steinwald and Sloan, 1974; Pauly and Satterthwaite, 1981; Reinhardt, 1985; Stano, 1985; McGuire and Pauly, 1991; McGuire, 2000). Indeed, the idea of a target (by itself) is strongly questionable: why would a physician set a target income? How would it be set? (McGuire and Pauly, 1991). These authors conclude that "Health economists can debate the size of income effects, without having to explain the absurd behavior which underlies the literal target income hypothesis" (p. 406). Steinwald and Sloan (1974) conducted an empirical study of the determinants of physicians' fees; their results are not consistent with the target income hypothesis, and they suggest a profit-maximizing-type model.

PID and target income theory provide some arguments for the existence of a physician's market power. However, other elements can create a monopolistic competitive environment.

2.2 Quality as a source of market power

Another element that can explain the ambiguous relationship between density and price in the healthcare market is the differentiation of services provided by physicians. A growing body of literature has developed around the notion of quality competition, and a comprehensive review can be found in Sivey and Chen (2019). A way for physicians to reduce the competitive pressure induced by a more competitive environment is to increase the quality of their services (reduced waiting time, better reception, longer consultation, etc.). If patients value quality, physicians can enter into a quality competition game that could result in a higher average price. Quality competition would then explain a positive relationship between price and physician density. This idea that quality explains the correlation between physician concentration and level of fees is not new[3]. This link has been extensively studied theoretically and empirically by Hugh Gravelle during the last two decades, but we focus here on his latest contributions. Gravelle et al. (2016) analyses the effects of competition on prices and quality of GP consultations using individual Australian data. The Australia case is interesting, as this is the only country where all practitioners balance their bills. They first develop a Vickrey-Salop model where GPs simultaneously choose both price and quality. In this model, GPs observe the taste for the quality of patients and based on that are able to implement perfect price discrimination. Data are taken from a large survey, and quality is measured by the length of the consultation. Contrary to most physician market studies that used physician density as a measure of competitive pressure, the authors construct individual GP measures of competition based on the distance to the third (and fifth) nearest GP. They find a negative relationship between competition and price[4] but no significant relationship between competition and quality. In a most recent paper, Gravelle et al. (2019) analyze the link between competition and quality using more than 8,000 UK GP data over the period 2005-2012. As in the UK, prices are regulated, and patients face zero fees; thus, there is no possible price competition. This is a perfect setting to evaluate the existence of quality competition. Indeed, in that case, encouraging competition amongst health care providers will improve quality, as higher quality is then the only way in which practitioners can attract more patients. They define the area of competition for a GP as a fixed radius of 2 km, and the quality of GPs is measured using responses to three questions from the survey. On this dataset, they find that an increase in the number of rival practitioners and quality are positively associated, especially concerning patient satisfaction. These two important studies seem to identify a link that exists between competition and quality if there is no price competition. This idea seems to be confirmed by Sivey and Chen (2019). They point out that in most contexts, quality is indeed a determinant of patient choice of provider, and therefore, the prerequisites of quality competition are met. Nevertheless, they also point out that empirical studies provide mixed results concerning the link between the level of competition and the level of quality (see Johar, 2012, on Australia's GPs). From a theoretical perspective, physicians have an incentive to improve their quality if they are to attract more patients. This works if 1) patients value quality (which is supported by empirical evidence) and 2) physicians are below capacity, that is, if they can accommodate any extra patients, they attract them by raising their quality levels. As pointed out in Sivey and Chen (2019), this last assumption may seem implausible for many parts of the health market where waiting times are high (Siciliani et al., 2014).

[3] Feldman and Sloan (1988) assume that doctors in large markets are more specialized than those in small markets and are therefore more expensive.

[4] That is, higher competition leads to lower prices.

2.3 The lack of unbiased econometric methods used in the healthcare pricing literature

Although the problem of local market characteristics measures has been widely discussed among economists to invalidate the support of some theoretical arguments, less attention has been paid to the econometric estimators and techniques used. In this paper, we want to focus on one of these techniques: the introduction of spatial dependence among competitors through spatial econometric models. Application of spatial econometric techniques in empirical studies on healthcare pricing is scarce, even if the implied potential bias is huge (see Baltagi et al., 2018, for an example). Indeed, to the best of our knowledge, there is no paper to date that has taken into account the spatial dependence between physicians' pricing decisions, and only three studies use those methods on hospital data. Mobley et al. (2009) analyze the importance of spatial interaction in hospital price competition using US data. They highlight a strong positive link between the Herfindahl-Hirschman Index (HHI) concentration measure and the pricing of hospitals. However, more interestingly, they show how accounting for spatial dependence is crucial to properly estimate the effect of competition intensity on price. They compare the results obtained with the OLS estimator without spatial dependence and the ML estimator with spatial dependence. Two spatial weight matrices are used to define the link between hospitals: the 7 closest neighbors and the inverse distance. It appears that the OLS results lead to upward bias in the estimated parameters of approximately 18%. The spatial lag parameter is estimated to be approximately 0.3, suggesting that hospital prices are strategic complements. It also provides a measure of imitative pricing existing between neighboring hospitals. Indeed, price increases in a hospital will lead neighboring hospitals to increase their price regardless of the level of competition in the area.

In a more recent study of UK hospitals, Gravelle et al. (2014) evaluated the importance of spatial interaction in hospital quality competition. To construct the link between hospitals, they built a row-standardized inverse distance matrix with a 30-minute travel time threshold. Their results were obtained using an ML estimator and show that for seven of the 16 quality indicators, quality is a (significant) strategic complement between hospitals, and they find no cases where quality could be a strategic substitute. The third and final paper using spatial econometric techniques is the paper of Longo et al. (2017) using a panel of UK hospital data. In this paper, they evaluate whether hospitals change their quality or efficiency in response to changes in the quality or efficiency of neighboring hospitals. They use a row-standardized inverse distance matrix with a 30 km threshold to define the competition area of hospitals. Using data on eight quality measures and six efficiency measures, their empirical results do not suggest that hospitals' quality or efficiency respond to rivals' quality or efficiency, except for the hospital's overall mortality.

3 A circular city model with heterogeneous physicians

3.1 General framework

We model physicians' pricing decisions within an area by combining different circular city models. We use a heterogeneous cost framework similar to that proposed by Alderighi and Piga (2008, 2012, 2014) and Lin and Wu (2015) to allow physicians to set different prices within the same area that we observed in reality. Our model is also inspired by the Gravelle et al. (2016) model in the sense that we introduce another source of heterogeneity: consultation quality. Our model departs from Gravelle et al. (2016), as we consider the physician's consultation quality as given. Even if this assumption may appear strong, we think that it better describes reality for at least three reasons. First, consultation quality is highly dependent on physicians' endowments, such as university education, and their vision of what quality is. Most of these factors are determined before physicians start to practice and are unlikely to change. Second, consultation quality is a multidimensional notion that involves both technical (objective) and nontechnical (nonobjective) aspects of care (see Haddad et al., 2000; Arneill and Devlin, 2002; Levine et al., 2012). Consequently, patients' views on the quality of a physician's consultation seem to be a better proxy for evaluating quality of care than purely technical physician measures of quality. Finally, in their literature review on competition and quality in healthcare, Sivey and Chen (2019) highlight that empirical studies unambiguously show that patients tend to choose higher-quality providers, but they are not able to highlight the existence of quality competition in healthcare.

We consider a circular city of length L. In this city, there are H patients who are uniformly distributed around the market and there are $N > 1$ equally spaced physicians. Thus, the density of the patients at any point in the market is given by $h = H/L$, and the distance between each physician is given by $l = L/N$. Consumers are indexed by their own locations, which represent taste. Under the National Health Insurance (NHI), a physician $i \in \{0, 1, ..., n\}$, with $n = N - 1$, receives a gross fee per consultation of $p_i + \overline{p}$, where $\overline{p}$ is the rebate amount from the NHI and p_i is the net price paid by the patient. We assume that patients demand at most one consultation per period from their physician and that they are sensitive to both the net price and the quality of the consultation. Without loss of generality, let physician i be located at $l_i = i \times l$ and offer a consultation of value v at net price p_i with a quality q_i. Physicians set prices simultaneously. Let a patient's transportation cost be linear over the (Manhattan) distance between the physician and the patient at rate t. Thus, a patient located at x choosing physician i derives the following utility:

$$u_i(x) = v - p_i + \alpha q_i - td_i, \; d_i \equiv \mid l_i - x \mid . \tag{1}$$

In this model, we consider that the information on the consultation quality of physicians is perfectly known by patients in the city thanks to reputation and public information available (through online ratings, physicians' website, etc.). In this sense, q_i can also be seen as the perceived consultation quality of physician i. We also assume that v is large enough to ensure that all patients demand a consultation. In the remainder of this paper, the discussion on price competition refers to the role of the different sources of differentiation on the incentives to compete in price.

Accounting for heterogeneity in physicians' costs (c_i) and quality (q_i), and following the convention in the literature (see Alderighi and Piga, 2008, 2012, 2014), we examine the equilibrium at which all physicians obtain a positive market share. Thus, we impose the following condition throughout the paper to rule out cases in which an existing physician cannot actively compete with other physicians:

$$\mid p_i - p_{i+1} \mid < tl - \overline{p}, \quad \forall i \in \{0, 1, ..., n-2\}. \tag{2}$$

For notational convenience, we extend the domain of i, such that $i \in \mathbb{Z}$, to allow for continuous increments to physicians' indices. Physicians i and $i \pm n$ denote the same entity.

3.2 Equilibrium when cost and quality are independent

We follow Alderighi and Piga (2008) by keeping the requirement that competition is localized, that is, the market share and price of a physician located in i is directly affected only by the behavior of the two adjacent physicians. Consequently, the demand for physician i depends on its price (p_i), its quality (q_i) and the price and quality of its immediate neighboring physicians. Standard computations yield physician i's demand (Tirole, 1988, p. 283):

$$D_i = h\left[l + \frac{p_{i+1} + p_{i-1} - 2p_i + \alpha[2q_i - q_{i+1} - q_{i-1}]}{2t}\right].$$

The profit of a representative physician is thus:

$$\pi_i = (p_i + \overline{p} - c_i)D_i = (p_i + \overline{p} - c_i)h\left[l + \frac{p_{i+1} + p_{i-1} - 2p_i + \alpha[2q_i - q_{i+1} - q_{i-1}]}{2t}\right]. \tag{3}$$

Proposition 1:

There exists a unique equilibrium among n physicians. For physician i, $i \in \{0, 1, ..., n-1\}$, we have

$$p_i^* + \overline{p} = tl + \alpha q_i + \sum_{d=0}^{n-1} b_d[c_{i-d} - \alpha q_{i-d}], \tag{4}$$

where

$$b_d = \frac{(2+\sqrt{3})^d + (2+\sqrt{3})^{n-d}}{\sqrt{3}[(2+\sqrt{3})^n - 1]} > 0$$

and physician i's profit is

$$\pi_i^* = h\frac{(p_i^* + \overline{p} - c_i)^2}{t}.$$

The proof of Proposition 1 is provided in the supplementary content (see Appendix A). The equilibrium price p_i^* shows that each physician's pricing strategy depends not only on each own quality and cost but also on the quality and costs of all the other physicians in the market. This highlights the chain-linked effect discussed in Chamberlin (1949) and Rothschild (1982). Indeed, physicians pricing strategies and profits are directly affected by their first-degree neighboring rivals, who also compete directly with their neighbors, who are second-degree neighbors to the original physician. Consequently, competition propagates around the circle and links all physicians' pricing strategies together. The coefficients, b_d, analytically quantify the impact of heterogeneous quality and costs on each physician's equilibrium price and profit. Thus, b_1 is the magnitude of the direct impact from a first-degree neighbor, whereas b_d $(d > 1)$ represents the indirect impact originating from a physician located further away with d degrees of separation from the affected physician (see Figure 1 below).

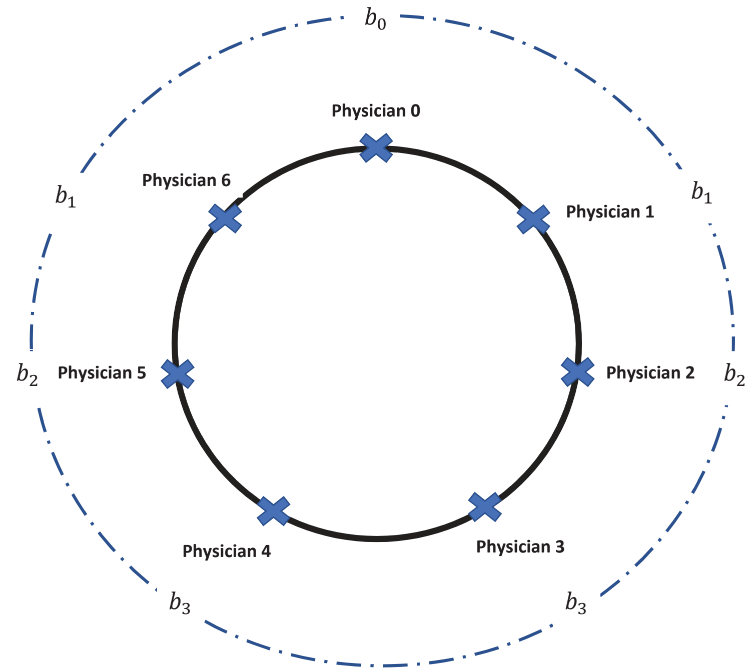

Figure 1: The circular city framework (Physician 0's perspective)

Corollary 1:

(a) $\frac{\partial p_i^*}{\partial c_{i-d}} = \frac{\partial p_{i\pm d}^*}{\partial c_i} = b_d > 0$ for $d = 0, 1, ..., n-1$. An increase in any physician's cost leads to a higher equilibrium price for all physicians, thus implying that a higher cost structure is associated with lower price competition in the market.

(b) $\frac{\partial p_i^*}{\partial q_{i-d}} = \frac{\partial p_{i\pm d}^*}{\partial q_i} = -\alpha b_d < 0$, for $d = 1, ..., n-1$ and $\frac{\partial p_i^*}{\partial q_i} = \alpha(1 - b_0) > 0$. An increase in any physician's quality increases its equilibrium price but leads to a lower equilibrium price for all other physicians. It thus implies that higher quality is associated with higher price competition in the market.

(c) $b_d > b_{d'}$ if $\min\{d, n-d\} < \min\left\{d', n-d'\right\}$. The effect of quality and cost weakens as it reaches physicians that are farther away from the originating physician.

(d) $0 < b_0 < 1$ and $\sum_{d=0}^{n-1} b_d = 1$. When a physician's cost and/or quality change, only part of these changes are absorbed by the physician's price. The remaining cost and quality changes are fully captured by the rest of the physicians.

(e) $\frac{\partial b_d}{\partial n} < 0$. When competition increases, the effect of quality and cost weakens.

The subscript $i \pm d$ refers to the dth-degree neighbor on either the left or right side of the physician.

The Corollary 1 results highlight an opposite impact of vertical and horizontal differentiation.

A physician with a higher cost is obliged to set a higher price to realize profitability. Consequently, this elevated price mitigates the physician's price competition with its first-degree neighbors, who are incited to set higher prices too. The incentive to set high prices is then transferred from physician to physician around the circle, resulting in a higher price for all physicians (everything being equal).

A physician with higher quality benefits from stronger patient demand. Consequently, this higher quality increases the physician's price competition with its first-degree neighbors, who are impelled to set a lower price to keep their market share. The incentive to set lower prices is then transferred from physician to physician around the circle, resulting in a lower price for all physicians (everything being equal).

As shown in Lin and Wu (2015), the impact of a physician's cost and quality on other physicians' prices weakens quickly as it travels further away from the originating physician. This implies that a physician's price is affected primarily by the physician's first- and second-degree neighbors. This is consistent with the result obtained by Alderighi and Piga (2012).

3.3 Equilibrium when cost and quality are linked

In this section, we introduce a formal link between the cost function and a physician's consultation quality. This will allow us to obtain more testable predictions but also to simplify the model. More importantly, we cannot reasonably assume a total disconnect between physician cost and physician consultation quality. According to a report provided by Hensgen et al. (2000) for France, the structural costs of all specialist physicians break down as follows: approximately 20% for rental (building and materials), 30% for general expenses, 20% for staff costs and 30% for taxes and payroll. We can easily assess that physician consultation quality influenced the physician's cost structure in terms of staff, materials, building and general expenses. The cost function is also influenced by elements related to the environment where the physician operates. Indeed, rental and staff costs are influenced by the physician's location. Based on 102 studies, Ahlfeldt and Pietrostefani (2019) provide a meta-analysis of the elasticity of 15 main outcomes with respect to the population density. They suggest an elasticity of 21% for the rental value and of 4% for wages, suggesting that rent price and wages are effectively higher in denser areas. For France, Combes et al. (2018) also highlight the positive link between population in cities and house and land prices. Taking into account these elements, we propose the following cost function for a physician:

$$c_i = \beta q_i + \delta^{'} Z_i, \qquad \beta > 0, \tag{5}$$

where q_i is the (perceived) consultation quality for physician i and Z_i is a set of variables that influence physician cost, including personal, location specificities, taxes and payroll.

If we replace this expression in the previous equilibrium price (4), we obtain:

$$p_i^* + \overline{p} = tl + \delta^{'} Z_i + \theta q_i + \eta \sum_{d=1}^{n-1} b_d q_{i-d}, \tag{6}$$

where

$$b_d = \frac{(2+\sqrt{3})^d + (2+\sqrt{3})^{n-d}}{\sqrt{3}[(2+\sqrt{3})^n - 1]} > 0, \qquad \theta = \alpha + \eta b_0, \qquad \eta = \beta - \alpha.$$

This last expression highlights in a more comprehensive way how consultation quality influences physician price. First, the individual price increases with the quality of the physician because patients value it ($\theta > 0$). Second, the individual price is also influenced by the consultation quality of neighboring physicians (η). As quality influences both the supply and demand sides here, the net effect of neighboring quality is ambiguous and depends on two key parameters: the valuation of consultation quality by patients (α) and the impact of consultation quality on the cost of physicians (β).

Proposition 2:

The impact of consultation quality on individual prices strongly depends on the difference between the marginal effect of quality on patients' utility (α) and the marginal impact of quality on the physician's cost structure (β):

(a) If $\eta = \beta - \alpha > 0$, individual prices increase with both individual and neighbors' quality. In that case, vertical differentiation reduces price competition incentives in the local market.

(b) If $\eta = \beta - \alpha < 0$, individual prices increase with individual quality but decrease with neighbors' quality. In that case, vertical differentiation increases price competition incentives in the local market.

Proposition 2 tells us that the valuation of quality by patients relative to the cost induced for physicians is at the heart of the pricing behavior of physicians in the local market. In the case where $\eta > 0$, the improvement of just one physician's consultation quality will be worse for most patients. Indeed, this quality move will reduce price competition in the local market and thus lead to a higher price for all physicians, whereas only one proposes a better care experience. Consequently, most patients will have to pay a higher price without benefiting from better care. The opposite situation occurs in the case where $\eta < 0$. Proposition 2 also highlights the important cumulative effects of vertical differentiation in the presence of horizontal differentiation. The importance of propagation effects described before depends directly on the value of $\mid \eta \mid$. We can measure the strength of these propagation effects as the relative impact of neighbors' quality on individual price, that is, the ratio $\rho =\mid \eta/\theta \mid$.

Corollary 2:

If $\eta > 0$, an increase in local competition intensity ($n \uparrow$):

(a) reduces the marginal effect of individual quality on price ($\partial\theta/\partial n < 0$).

(b) increases the relative importance of neighboring quality on individuals measured by $\rho = \eta/\theta$.

If $\eta < 0$, an increase in local competition intensity ($n \uparrow$):

(c) increases the marginal effect of individual quality on price ($\partial\theta/\partial n > 0$).

(d) decreases the relative importance of neighboring quality on individual prices measured by $\mid \rho \mid$.

Note that competition intensity only influences ρ through the marginal effect of individual quality on price, denoted θ in (6). Indeed, competition intensity does not influence the marginal effect of neighbors' quality on individual price, denoted η in (6).

3.4 Equilibrium price in a circular city model: A structural spatial model

As suggested by Alderighi and Piga (2012, p. 57), the equilibrium price of a circular-city model with heterogeneous agents can be rewritten in the form of a model with a spatial lag of the dependent variable, i.e., the spatial lag of physician prices in our case. To the best of our knowledge, no paper has proposed this corresponding expression, but it could be very useful from an empirical estimation perspective (we later discuss this point in detail; see the identification strategy section).

Proposition 3: The equilibrium price of a circular-city model can be rewritten as a type of structural spatial lag model (SLM hereafter). In our particular case, the equilibrium price equation is given by:

$$P_i^* = C + \rho \sum_{d=1}^{n-1} b_d P_{i-d}^* + \phi q_i + \lambda \sum_{\tilde{d}=1}^{n-1} w_{\tilde{d}} q_{i-\tilde{d}}, \tag{7}$$

where $P_i^* = p_i^* + \overline{p}$ and

$$b_d = \frac{(2+\sqrt{3})^d + (2+\sqrt{3})^{n-d}}{\sqrt{3}[(2+\sqrt{3})^n - 1]}, \qquad w_{\tilde{d}} = \sum_{d \neq \tilde{d}}^{n-1} b_d b_{n+\tilde{d}-d}, \quad d \in \{1, ..., n-1\},$$
$$C = \left[1 - \frac{\eta(1-b_0)}{\theta}\right](tl + \delta' Z_i), \qquad \rho = \frac{\eta}{\theta}, \qquad \phi = \theta - \frac{\eta^2}{\theta} w_0 > 0, \qquad \lambda = -\frac{\eta^2}{\theta} < 0.$$

The proof of Proposition 3 is presented in the supplementary material (see Appendix A). In this last expression, C includes all variables influencing the physician's cost (Z_i) and the average distance between physicians (l). ϕ represents the influence of individual quality on price, whereas λ represents the residual influence of neighbors' quality. Finally, ρ, which measures the spatial dependence in price, corresponds to the relative impact of neighbors' quality with respect to individual quality on individual price (see Proposition 2 and Corollary 2).

Proposition 3 highlights that, fundamentally, the circular city model with heterogeneous physicians does not correspond to a simple spatial lag model (SLM), as suggested by Alderighi and Piga (2012, p. 57). Indeed, equation (7) highlights two types of spatial dependence in the pricing decision of a physician. The first discussed by Alderighi and Piga (2012, p. 57) is related to the spatial lag of price ($\sum_{d=1}^{n-1} b_d P_{i-d}^*$). As our model includes both horizontal and vertical differentiation, we cannot theoretically assess the net effect of the spatial dependence in price.[5] The second spatial dependence is related to a combination of neighboring consultation qualities ($\sum_{\tilde{d}=1}^{n-1} w_{\tilde{d}} q_{i-\tilde{d}}$). This second spatial dependence unambiguously reduces the equilibrium price as $\lambda < 0$.

Corollary 3:

(a) $\mid \rho \mid$ measures the strength of the link between individual prices and neighboring prices.

(b) if $\rho > 0$, prices are strategic complements, and $\mid \rho \mid$ can be seen as a measure of **imitative pricing**.

(c) if $\rho < 0$, prices are strategic substitutes, and $\mid \rho \mid$ can be seen as a measure of **nonimitative pricing**.

This interpretation of the sign of ρ is supported by the fact that in the original price equilibrium (6), ρ is a measure of the relative impact of neighbors' quality on individual price. Moreover, the sign of ρ tells us about the role of consultation quality on the incentive for physicians to engage in price competition. In the next section, we present the data used to estimate ρ and the structural price equation in detail.

4 Institutional context, data collection and descriptive statistics

4.1 Organization of the French primary care system

The French health care system is an excellent experimental context in which to study physicians' pricing behavior. Doctors are paid on a fee-for-services basis, with many specialists able to determine their own fees. On the demand side, the patients' choice of health care providers is unrestricted.

The level of the regulated fee is the same country wide and is negotiated at the national level between physician unions and the national health insurance (NHI) system. However, there are two categories of doctors in France: "Sector 1" or "fee-regulated physicians" who must respect the regulated fee and "Sector 2" or "free-billing physicians" who can bill above the regulated fee but are obliged (theoretically) to respect a certain level of "tact and moderation" and to not balance bill low-income patients.[6] The choice of sector has to be made at the beginning of the career, but there are some training and qualification requirements[7] to be eligible for Sector 2. Consequently, Sector 2 physicians are supposed to be more qualified (and thus provide better quality consultation) than Sector 1 physicians.

Patients are free to choose their physician but must designate a referring doctor, usually a general practitioner (GP), to act as a gatekeeper. However, for a limited number of specialists: gynecologists, pediatricians, ophthalmologists, psychiatrists and dentists' patients do not need to be referred by their referring doctor to be reimbursed by NHI. Every citizen is covered by NHI, and all citizens are free to subscribe to private health insurance that pays (partially or totally) the difference between what is covered by NHI (70% of the regulated fee) and what the physician charges. Note that approximately 90% of the population has private

[5] Circular city models such as Alderighi and Piga (2008, 2012, 2014) or Lin and Wu (2015) only consider horizontal differentiation (through heterogeneous cost) so that heterogeneity only influences the supply side and covers all the cost functions. From a mathematical perspective, this means they assume that $\alpha = 0$ and $\beta = 1$. In our case, heterogeneity directly influences both the supply ($\beta > 0$) and the demand side ($\alpha > 0$), and we do not impose that all costs are fully heterogeneous, as we allow some part of the physician's cost to be common at the city or higher geographical level ($\beta \neq 1$).

[6] A small percentage of Sector 1 physicians have a "permanent right to balance bill"; in this study, they are classed as Sector 2 doctors.

[7] The Sector 2 system was created in 1980 and was open to all physicians until 1990. After this date, the government implemented some requirements to have access to Sector 2.

health insurance in France. In the case of patients with private insurance, Sector 1 physician charges are fully reimbursed;[8] however, as NHI does not cover the additional fees imposed by Sector 2 doctors, depending on their insurance contract, patients have to pay these additional fees partially or totally. During our period of interest (2013), the regulated price for any doctor was 23 euros (plus a lump-sum payment of 5 euros for specialists).

Although the share of GPs who can balance bill their patients is less than 10%, it is true for more than 40% of specialists (Caisse Nationale d'Assurance Maladie, CNAM, 2011). On average, in the case of specialists, the additional fee amount was equal to 52% of the regulated fee in 2016 vs. 25% in 1990 (CNAM, 2014; CNAMTS, 2017). We focus on three different specialists, namely, pediatricians, ophthalmologists and gynecologists; according to CNAM (2011); CNAMTS (2017), the share of Sector 2 physicians was 32%, 53% and 49%, respectively in 2010, and additional fees represented 67%, 61% and 100% of regulated fees in 2011, respectively.

4.2 Data collection and sample used

Physicians database

Our main dataset was created by UFC-Que Choisir, the leading French consumer union, which collected information provided by the French NHI's website (AMELI) to help patients choose their physician. The database contains price information for private physicians in three specializations (ophthalmology, gynecology and pediatrics) for 2013. For every physician, this unique dataset contains information on their gender, type of activity (liberal only or liberal and hospital), "sector", address and fee level. Note that price information retained for this study corresponds to "the fee generally recognized for the main activity" in the CNAM definition. In other words, we consider only the price of a "standard consultation", which gives us a comparable basis for physician services. Our observed population of physicians is composed of 2,106 pediatricians (745 in Sector 2), 3,933 ophthalmologists (2,174 in Sector 2) and 4,237 gynecologists (2,464 in Sector 2).

Physicians' environment data

To collect physician environmental data, we use the database "Comparateurs de territoires" (Benchmark of territories) that was provided by INSEE (National French Statistical Office). This database contains various types of statistical information at the city level (more than 36,700 in France), such as population, median income, and area (sq km). For the three main French cities (Paris, Lyon and Marseille), we have access to this information at the district level (20 for Paris, 16 for Marseille and 9 for Lyon). Consequently, we are able to precisely distinguish the differences in the environment for these three specific cities in France. In the most recent update (2017), population and income statistics are available for the years 2009 and 2014. As we have information on physician prices in 2013, we decided to use the 2014 values.

Geolocalization

For the geolocalization of physicians, we used the Geocoding API of Google to obtain the latitude and longitude of each address. A code using R software (available upon request) has been developed to automatically

[8] Except for a 1 euro copayment that insurance does not cover.

obtain this information. We then checked the precision of coordinates for every physician to reduce the error of geographical position. This last step was completed using Google Maps in combination with QGIS 3.16 (https://qgis.org/en/site/), a free and open-source cross-platform desktop geographic information system.

Physician's quality data

The consultation quality of a physician is a difficult characteristic to measure, as it involves numerous objective and nonobjective features. It is of first importance, as a measurement error in this variable could lead to endogeneity problems and biased estimates. In their seminal paper, Gravelle et al. (2016) measured the quality of a physician by the average consultation time for patients. If the duration of a consultation influences the quality, we cannot reasonably assess that duration is a good proxy for quality, especially if we want to determine the nonobjective measures that can be important for patients.

Online reviews are an interesting source for tracking the satisfaction of patients with medical services and their quality of care. Over the last few years, reviews of medical care have become a general tool to create more transparency surrounding the quality of physicians in the United States and other advanced countries (Greaves and Millett, 2012; Grabner-Kräuter and Waiguny, 2015; Emmert et al., 2016). McGrath et al. (2018), using a large-scale study for physicians from 10 of the largest cities in the United States, indicate that online patient ratings are consistent with physician peer review qualification for four nonsurgical and primarily in-office specializations. In this paper, we use the ratings made by patients available on Google as a proxy for consultation quality. We are, nevertheless, aware that this measure could also be subject to a number of biases (motivation bias, social bias, etc.), but we think this is probably the best proxy available.

Google ratings are a measure of patient satisfaction using a rating from 1 to 5 stars. To control for potential measurement error, we collect information of two physician indicators: average Google rating and total number of ratings. We collect this information manually, as Google does not allow us to automatically scrape this information. Ratings are not available for all physicians, which reduces our testable sample. More precisely, we were unable to obtain ratings for 149 pediatricians, 500 ophthalmologists and 602 gynecologists. Our final sample of free-billing (Sector 2) physicians therefore consists of 596 pediatricians (80% of original dataset), 1,674 ophthalmologists (77% of original dataset) and 1,862 gynecologists (76% of original dataset). This data collection was performed in 2018 and contains ratings of physicians from 2017 and before. Figure 2 presents, for each type of physician, the geographical coverage of the original dataset (black and red points) and the final sample (red points).

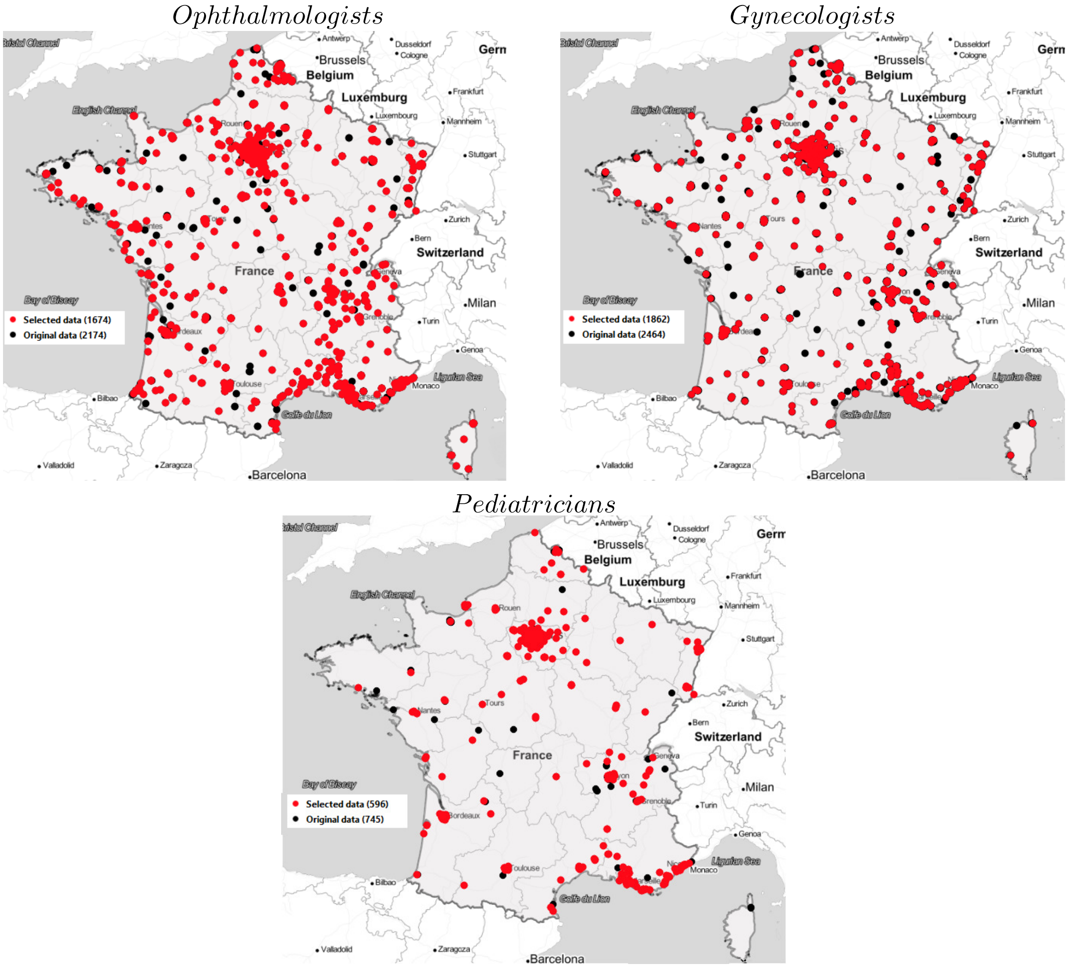

Figure 2: Geographical coverage: Original and selected data.

4.3 Descriptive statistics

Using our final sample, we generate maps of the average physician's price. The spatial distribution of the price was created by applying an interpolation inverse distance weighting (IDW) algorithm. The results of this procedure are shown in Figure 3 for the Paris region.[9] The IDW procedure[10] is a deterministic method for multivariate interpolation with a located set of points. We divide the area of France into pixels of 150×150 squared meters, and we assigned values to unknown pixels using the weighted average of the values available at each observed point.

[9] We also created such maps for all of France. Nevertheless, given the high spatial concentration of physicians across the territory, it does not make sense to use this method for the full territory.

[10] The IDW formula is given as $\widehat{z} = \sum_{i=1}^{N} dist_i^{-\alpha} z_i / \sum_{i=1}^{N} dist_i^{-\alpha}$, where $\widehat{z}$ is the estimated value for the prediction point, z_i is the observed value for the sample point, $dist_i$ is the Euclidean distance between sample point i and the prediction point, α is an exponential factor and N is the number of sample points. In our case, the exponential factor used in the inverse distance was set to 1.

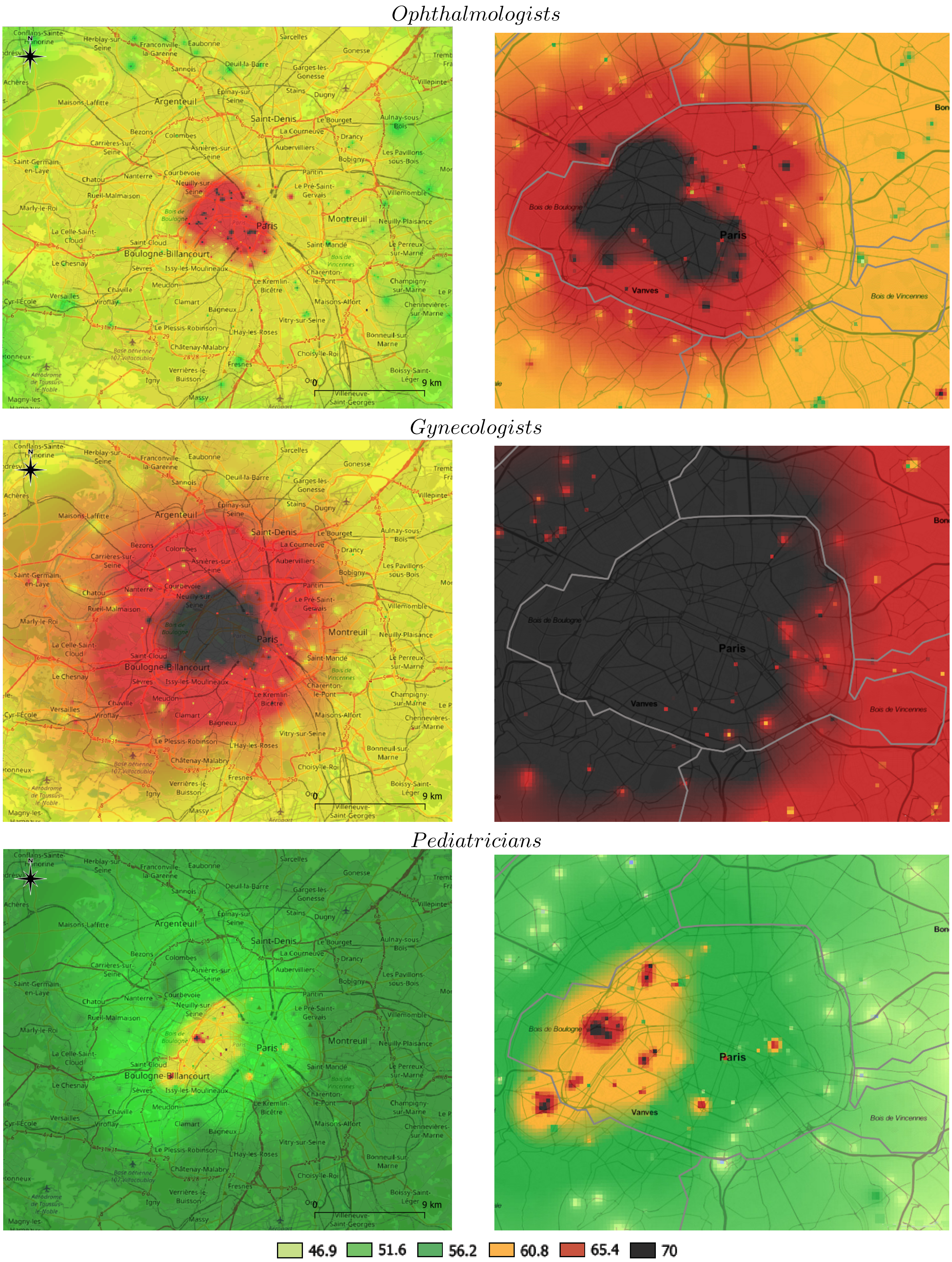

Figure 3: Interpolation of average price of physicians in Paris region.

As we can see from the maps in Figure 3, the geography of physicians' prices in the Paris area is quite uneven. These three maps clearly highlight the nonrandom nature of physician prices and the importance of geography's weight in their determination.

In Table 1, we present the summary statistics of the main variables present in the database constructed and used in empirical estimation. The first is the variable PRICE, which measures the average price for a standard physician's consultation. GENDER is a dummy variable taking a value of 0 for men and 1 for women. LIBERAL is also a dummy variable taking a value of 0 if the physician works both in its private office and in a hospital and 1 if they only work in their office. MEDIAN represents the median income (in thousands of euros) in the city where the physician operates. DPOP measures the density of the population obtained from the division of the total population (in thousands) by the city's area. These two last variables aim to control for local demand characteristics that also influence physicians' costs.

ADISTANCE measures the average distance between a physician and its rth-degree neighbors (in km). This measure takes into account both physicians in Sector 1 and Sector 2. We report this variable for 1st degree, 1st and 2nd degree and finally 1st, 2nd, and 3rd degree neighbors. SHARE2 represents the share of free billing in a physician's rth-degree neighbor. These last two variables aim to measure the intensity of competition for a particular physician. The advantages of those measures are numerous. First, they are specific physicians, unconstrained by administrative boundaries. Second, ADISTANCE is the best fit with the theoretical average distance (l). Third, as described in Gravelle et al. (2016, p.150), the use of such individual distance as a measure of competition reduces the potential endogeneity problem related to the link between competition intensity and individual location choice.

RATING is a measure of average Google ratings obtained by the physician, and C-RATING represents the number of ratings received.

As we can see in Table 1, there are important differences between physicians' prices according to the specialty. Indeed, the average price observed for gynecologists stood at more than 55 euros per consultation, whereas this average price was just 45 euros for pediatricians. Ophthalmologists are between these two specializations with an average price just over 49.5 euros. These differences do not concern only price. Regarding gender, women represent 53% and 50% of pediatricians and gynecologists, respectively, but only 32% of ophthalmologists. The share of physicians operating only privately is above 60% for ophthalmologists and gynecologists but near 50% for pediatricians. Concerning the city's characteristics, it seems that pediatricians are more concentrated in areas with greater population density and median income than gynecologists and ophthalmologists. This is mainly due to the lower number of practitioners in this specialty linked to a much smaller patient target. In terms of competition intensity, the average distance from first-degree neighbors is 6.8 km for ophthalmologists, 6.59 km for pediatricians and 4.35 km for gynecologists. Obviously, the average distance increases when we consider higher degree neighbors. The composition (in terms of sector) of first-degree neighbors is clearly different between specializations. Indeed, whereas the share of Sector 2 physicians represents 46% of local competitors for pediatricians, it stands at 64% for gynecologists and 56% for ophthalmologists. This rank between specialists remains when we consider higher-degree neighborhoods. It is interesting to note a strong correlation between the price and the composition of the local neighborhood.

Variables	Mean	S.D.	Min	p25	Median	p75	Max
			Ophthalmologists				
Price	49.55	14.83	28.00	40.00	46.00	55.00	200.00
Gender	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Liberal	0.67	0.47	0.00	0.00	1.00	1.00	1.00
Median	22.56	6.05	13.26	18.57	20.42	24.95	42.77
Dpop	6.40	8.03	0.02	1.18	3.54	7.81	41.29
Adistance							
Order 1	6.80	12.28	0.03	0.54	1.63	7.52	125.06
Order 2	14.56	20.79	0.14	1.39	4.74	21.79	163.28
Order 3	24.39	29.58	0.58	2.68	10.71	40.06	222.28
Share S2							
Order 1	0.56	0.28	0.00	0.33	0.57	0.80	1.00
Order 2	0.53	0.22	0.00	0.35	0.53	0.69	1.00
Order 3	0.51	0.20	0.06	0.36	0.5	0.65	0.97
Rating	3.45	1.10	1.00	2.70	3.50	4.30	5.00
C-Rating	11.92	22.23	1.00	3.00	6.00	13.00	402.00
			Gynecologists				
Price	55.41	16.51	28.00	45.00	50.00	60.00	135.00
Gender	0.50	0.50	0.00	0.00	0.00	1.00	1.00
Liberal	0.63	0.48	0.00	0.00	1.00	1.00	1.00
Median	22.97	6.45	13.06	18.53	20.48	26.63	42.77
Dpop	7.56	8.59	0.02	1.81	4.18	9.86	41.29
Adistance							
Order 1	4.35	9.05	0.01	0.41	0.99	3.61	119.13
Order 2	10.41	15.90	0.06	1.08	3.04	12.99	137.15
Order 3	18.84	24.49	0.23	2.18	6.84	29.08	184.63
Share S2							
Order 1	0.64	0.28	0.00	0.44	0.67	0.86	1.00
Order 2	0.60	0.24	0.00	0.43	0.64	0.79	1.00
Order 3	0.58	0.22	0.06	0.41	0.61	0.77	0.97
Rating	3.77	1.05	1.00	3.10	4.00	4.70	5.00
C-Rating	13.28	21.85	1.00	4.00	8.00	14.00	342.00
			Pediatricians				
Price	45.06	14.06	28.0	35.50	42.50	50.00	117.50
Gender	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Liberal	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Median	24.09	6.16	13.21	19.01	23.00	28.66	42.77
Dpop	8.58	9.34	0.07	2.09	4.72	11.06	41.29
Adistance							
Order 1	6.59	12.15	0.07	0.94	1.84	5.08	91.61
Order 2	14.02	21.33	0.42	2.07	4.10	16.49	160.52
Order 3	23.40	30.73	1.15	3.16	8.41	34.37	197.15
Share S2							
Order 1	0.46	0.29	0.00	0.25	0.43	0.67	1
Order 2	0.43	0.23	0.00	0.25	0.43	0.57	1
Order 3	0.41	0.20	0.00	0.25	0.40	0.54	0.88
Rating	4.01	0.94	1.00	3.40	4.10	5.00	5.00
C-Rating	8.26	7.56	1.00	3.00	6.00	12.00	69.00

Table 1: Descriptive statistics of variables.

The final two variables concern the consultation quality of physicians. As we can see in Table 1, the average Google rating is strongly specialty dependent. The average pediatrician rating is 4.01/5, whereas the average gynecologist rating is 3.77 and for ophthalmologists is only 3.45. We may think that these differences are strongly influenced by a bias related to the number of ratings, but the descriptive statistics do not support this idea. Indeed, pediatricians have more than 8 ratings on average, ophthalmologists have nearly 12 and gynecologists have more than 13.

5 Empirical models and identification strategy

5.1 Empirical specifications and spatial matrices

The general specification

Our main empirical objective is to test the structural equilibrium price of our circular-city model developed in Section 3. More precisely, we will test the SLM version of this equilibrium price given by (7):

$$P_i^* = C + \rho \sum_{d=1}^{n-1} b_d P_{i-d}^* + \phi q_i + \lambda \sum_{\tilde{d}=1}^{n-1} w_{\tilde{d}} q_{i-\tilde{d}} \,,$$

where C includes all variables influencing the physician's cost (Z_i) and the average distance between physicians (l) and ρ measures spatial dependence among prices, that is, the link between individual and neighborhood prices. We remind the reader that, theoretically, the sign of the ρ coefficient informs us of the role of consultation quality on price competition in the market[11]. If ρ is negative, then physicians evolve in a market where quality drives price competition and thus increases nonimitative pricing. In contrast, if ρ is positive, then physicians evolve in a market where quality reduces price competition and thus increases imitative pricing. ϕ measures the marginal effect of individual quality, and λ represents the residual influence of neighbor quality after controlling for spatial dependence in price (see Mobley et al., 2009).

The advantage of using expression (7) of the equilibrium price instead of (6) is a first importance from an econometric perspective. Indeed, it is well known (and well described in Mobley et al., 2009) that ignoring spatial dependence will lead either to an upward bias (if $\rho > 0$) or a downward bias (if $\rho < 0$) in the estimation of the marginal effects of covariates. Indeed, naive estimation will consider as a marginal effect both the true marginal effect plus the spillover effect related to spatial dependence, leading to biased conclusions. Thus, it is necessary from an empirical perspective to estimate equation (7) instead of equation (6).

This leads us to propose the corresponding empirical model (compact form, see Appendix A):

$$p = \rho W p + XB + \phi q + \lambda \overline{q} + \varepsilon, \tag{8}$$

where X is a $n \times k$ matrix including individual and local market variables as well as dummies, W is a $n \times n$ spatial weighting matrix that measures the geographical distance between physicians (we discuss in detail this element in the next subsection), q is a $n \times 1$ vector of consultation quality and $\overline{q}$ is a combination of neighbors' quality defined as $\overline{q} \equiv [W \times W - diag(W \times W)]q$. Finally, ε is a $n \times 1$ vector of error term. We want to properly

[11] Indeed, $sign(\rho) = sign(\beta - \alpha)$; see equations (6), (7) and proposition 2.

estimate B, which is a $k \times 1$ vector of parameters related to independent covariates, ρ and λ, which are the spatial parameters, and ϕ, which is related to physician quality.

The creation of spatial matrices and competition variables

One limit of the circular city model is that it implicitly assumes that each city is an island so that no spatial dependence exists between physicians located in different cities. However, in reality, a physician i located in city a can be geographically closer to a physician j located in another city than a physician k located in city a. Spatial econometrics proposes using the spatial weight matrix W to capture the spatial dependence. Usually, the elements of W, w_{ij}'s, are nonzero when physician i and physician j are neighbors and zero otherwise. By convention, the diagonal elements are equal to zero, i.e., the self-neighbor relation is excluded:

$$W = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{2n} & \cdots & 0 \end{bmatrix}.$$

The creation of empirical spatial matrices W is, thus, of first importance to assess the true spatial dependence existing between physicians' prices. Consequently, we cannot use administrative boundaries such as cities to construct physicians' dependence areas.

To overcome this limitation, we divide the geographical space into artificial individual areas (irregular polygons). Each physician's area limits are defined by taking all points of the space that are closer to that physician than any other. This construction is called Thiessen polygons (or Voronoi diagrams). In economic geography, these polygons have been used as a quick and simple way to approximate market areas (Boots and South, 1997). Geometrically, the polygons are constructed by combining perpendicular lines at the midpoint of a line that connects a point to its nearest neighbors (the set of this connection is known as the Delaunay triangulation). From this construction, the most compact polygons are created, as shown in Figure 4. For more details see O'sullivan and Unwin (2010, pp. 50-52).

Consequently, we are able to define a specific dependence/competition area for each physician using Voronoi polygon contiguity. We decided to create three different contiguity matrices for each physician specialty. To define the neighborhood of a physician, the first matrix W_{1cont} uses the first-order (polygons) contiguity, the second matrix W_{2cont} uses the second-order contiguity and finally the last matrix W_{3cont} represents the third-order contiguity. For example, in Figure 4, we show in red the polygon of one specific physician. The first-order contiguity neighbors for this physician are those represented by polygons contained below the orange line. The second-order contiguity neighbors are represented by the polygons between the orange and light brown lines. Finally, the third-order contiguity neighbors are represented by the polygons between the light and dark brown lines. As noted by Alderighi and Piga (2012, p. 57), in circular city models, "propagation effects stop being economically important beyond the 2-step distance". Consequently, the best contiguity matrix will be the sum of W_{1cont} and W_{2cont}, which include all neighboring physicians until the second-order contiguity.

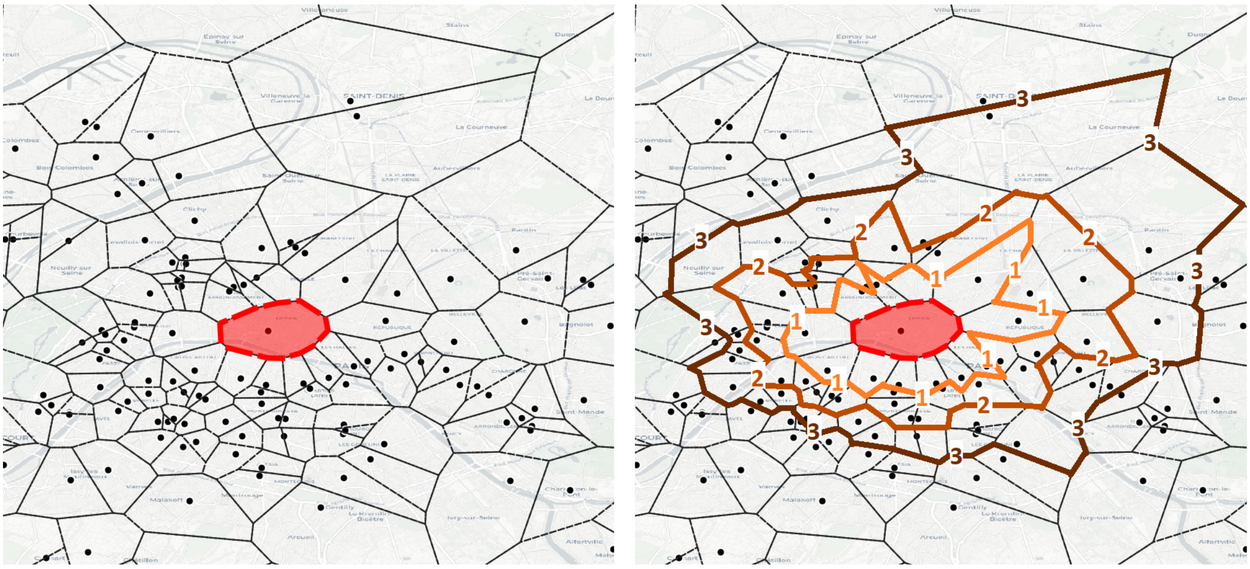

Figure 4: Example of Voronoi's tessellations under Euclidean distance.

The contiguity criterion only produces binary weights w_{ij}, which is not sufficient to define the spatial proximity between physicians. Thus, we also use a distance measure to capture the relative proximity. In this paper, we tried two well-known distance measures: the inverse distance and the exponential distance. The empirical results clearly point toward the exponential distance as the best weighting measure (from a data generating process (DGP) point of view), so we will focus on this measure in the remainder of this paper.[12] Using the exponential distance function, we define the w_{ij} between two physicians i and j as follows:

$$w_{ij} = \begin{cases} 0 & if\ \ i,j\ \ are\ \ not\ \ contiguous, \\ e^{-dist_{ij}} & if\ \ i,j\ \ are\ \ contiguous\ \ neighbors, \end{cases} \tag{9}$$

where $dist_{ij}$ is the Euclidean distance between physicians i and j.

Finally, our spatial weighting matrices defining the local competition area for each physician are obtained by combining the order of contiguity criterion with the distance function (9): W_1, W_{12} and W_{123} are the first-, first-second- and first-second-third-order contiguity with exponential weights. Additionally, we use W_{exp}, which is the exponential spatial matrix without contiguity restrictions. This last spatial matrix that links all physicians considering France as a unique market is used for robustness purposes. We provide detailed statistics on the characteristics of W spatial matrices in Table B.1 of Appendix B.

We also use Voronoi polygon contiguity to construct our two measures of competition. Indeed, we use rth-degree polygon contiguity and the distance in km to create ADISTANCE. However, contrary to the construction of spatial matrices that only link Sector 2 physicians, we consider all physicians in ADISTANCE. If we denote $W_{cont,i}$ as the $1 \times n$ vector of rth-order contiguity neighbors for physician i and D_i as the $1 \times n$ vector of the

[12]Results obtained with inverse distance are available upon request.

i-th row of the distance matrix D between all physicians, then, the average distance measure for physician i is defined as:

$$Adistance_i = \frac{W_{cont,i} \times D_i^{'}}{n_i} \tag{10}$$

where n_i is the number of rth-order contiguity physicians for physician i, and $'$ means transpose. We have three different measurements depending on the contiguity order. We build our second competition measure (Share S2) as the share of free-billing physicians in the rth-order contiguity neighbors defined previously. Then,

$$ShareS2_i = \frac{n_i^{S2}}{n_i} \tag{11}$$

where n_i^{S2} is the number of rth-order contiguity Sector 2 physicians for physician i.

For robustness checking purposes, we also create another measure of competition that combines both Adistance and Share S2. Indeed, we use rth-order polygons used to build spatial matrices that only consider Sector 2 physicians. If we denote $W_{contS2,i}$ as the $1 \times n$ vector of rth-order contiguity for physician i and D_i^{S2} as the $1 \times n$ vector of distance between physician i and the other sector 2 physicians, we can build:

$$Adistance_i^{S2} = \frac{W_{contS2,i} \times D_i^{'S2}}{n_i}. \tag{12}$$

Given the spatial weighting matrices defined previously[13] and competition measures, we propose different empirical models that will test three definitions of the local market for physicians:

Model 1: $p = \rho W_1 p + XB + \phi q + \lambda \overline{q}_1 + \varepsilon$, with $\overline{q}_1 = [W_1 \times W_1 - diag(W_1 \times W_1)]q$.

Model 2: $p = \rho W_{12} p + XB + \phi q + \lambda \overline{q}_{12} + \varepsilon$, with $\overline{q}_{12} = [W_{12} \times W_{12} - diag(W_{12} \times W_{12})]q$.

Model 3: $p = \rho W_{123} p + XB + \phi q + \lambda \overline{q}_{123} + \varepsilon$, with $\overline{q}_{123} = [W_{123} \times W_{123} - diag(W_{123} \times W_{123})]q$.

5.2 The identification strategy

In this section, we discuss how we handle numerous biases inherent to empirical estimation. Our main objective is to properly estimate our parameters of interest, especially ρ, λ and ϕ.

Sample selection bias

As described in the previous section, the availability of online ratings of physicians was partial. We work on a final sample covering approximately 80% of our initial sample, but this selection could be nonrandom. We thus implement the well-known Heckman two-step procedure to correct for potential sample selection bias. The first step consists of estimating the probability for a given physician to receive (at least) one Google rating using covariates and dummies as explanatory variables. We then compute the inverse Mills ratio obtained from the probit regression and include it in the final regression (Model 1-Model 3) as a covariate controlling for potential sample selection bias. In all estimations, we obtain a negative coefficient with respect to the inverse

[13] All matrices are row-standardized, as is usual in spatial econometrics.

mills ratio, which is significant for ophthalmologists and gynecologists. Consequently, for those two samples, "negative selection" occurred, and without correction, we would have produced a downward-biased estimate of parameters.

Location choice bias

An important element that can explain the price differences observed in different cities might be the result of location choice made by physicians. Indeed, if higher-quality physicians tend to colocate in areas with higher income, for instance, then the estimated relation between price and physician competition could be strongly biased without controlling for the location choices of physicians. Unfortunately, our dataset does not allow us to model this location choice. To limit the influence of this bias as much as possible, we include dummies at the city and district levels (Paris, Lyon and Marseille). Indeed, these dummy variables take into account all unobserved effects at this fine geographical scale, including the attractiveness of location for physicians. As the French territory is quite uneven in terms of physician distribution, a significant number of cities have just one physician. Consequently, we cannot control for city-level fixed effects for all physicians. Thus, we test three different types of location bias correction using 1) NUTS2 fixed effects, 2) NUTS3 fixed effects and 3) city/district fixed effects. The latter uses city fixed effects for those with at least two physicians. Obviously, we are more confident with the use of city and district fixed effects that control most of the unobservable effects at the finest level. Our preferred estimations will thus include those dummies.

Mismeasurement of covariates

Even if the measurement error has not been discussed deeply in empirical work, it can lead to endogeneity problems and, hence, biased estimates. To complete our empirical specification, we have to discuss which variables will be included to control for the local market characteristics to which a physician belongs.

Model (7) includes two main local market characteristics: the density of patients ($h = H/L$) and the distance between each physician ($l = L/N$) within the city. There are several problems in measuring these two variables and finding good proxies. To control for the demand side of the local market, we use the population density and the median income (see previous section for details) in the city/district where the physician operates. Concerning the supply side, as described in the previous section, we use two main proxies. The first is the average distance between a physician and its rth-degree contiguity neighbors (including both Sector 1 and Sector 2 physicians). The idea here is to control empirically for global competition facing every Sector 2 physician. The second is the share of Sector 2 physicians in the rth-degree contiguity neighbors. Here, our aim is to control for the competition structure by taking into account the importance of cheaper alternatives for patients.

One important covariate in our model is the consultation quality of a physician. We use the average Google rating given by patients as our proxy measure, which could be subject to a number of biases. To mitigate them, we control for the number of ratings received by each physician. Indeed, patients may value the information provided by the average rating more if they are based on more opinions.

Using the appropriate estimator

The coefficient ρ in (8) is the core (spatial) parameter to estimate. There are two main econometric techniques to address the endogeneity of the spatial lag of the dependent variable: (1) the maximum likelihood (ML) estimation method and (2) the generalized method of moment (GMM) estimation method. ML estimation is the most widely used technique (Anselin, 1988; LeSage and Pace, 2009). The GMM estimation (Kelejian and Prucha, 1998, 1999) has the advantage that it does not require any distributional assumption for the error term and remains computationally simpler than the ML estimator. Under the usual assumptions, i.e., independent and identically distributed errors, the ML estimator is relatively more efficient than GMM. However, both methods are inconsistent in the presence of heteroskedasticity in the error term. Nevertheless, Kelejian and Prucha (2010) extend their estimation approach by modifying the moment functions to obtain a robust GMM estimator under weaker distributional assumptions and unknown heteroskedasticity. Consequently, the GMM estimator proposed by Kelejian and Prucha (2010) is the most appropriate estimation method given the intrinsic heterogeneity of our model.

6 Empirical results, simulations and policy implications

6.1 GMM estimation of the empirical models

In this subsection, Table 2 presents the estimations of Models 1-3 for the three specializations using the exponential distance measure and city/district fixed effects (which better control for the location choice bias). The results using fixed effects at the NUTS2 or NUTS3 level are available upon request. In terms of overall performance ($RMSE$), it seems that Model 2 (first- and second-degree neighbors) is the best specification.

Concerning ophthalmologists, we detect a strong positive spatial dependence between ophthalmologist prices regardless of the definition of the local neighborhood. More precisely, the spatial lag coefficient is estimated to be between 0.329 (Model 1) and 0.396 (Model 3), implying that between 50% and 65%[14] of neighborhood prices are reflected in an increment of ophthalmologists' consultation price in the long run. In reference to our theoretical model, a positive ρ means that consultation quality reduces price competition incentives and that there exists significant imitative pricing in the ophthalmologist market. The importance of the spatial effect in ophthalmologist prices is also highlighted by the significant negative coefficient ($\hat{\lambda}$) associated with residual neighbor consultation quality ($\overline{\text{RATING}}$). As expected, the higher the neighboring consultation quality of a physician is, the lower its price, but due to high positive spatial dependence, this effect is very limited. Concerning the effect of individual quality (RATING), we do not detect a significant influence even if the number of online reviews matters (C-RATING). This does not mean that quality does not influence prices but instead that this effect is already reflected through the spatial dependence in prices leading to insignificant marginal direct effects. The positive, significant influence of the number of online reviews seems to highlight that physicians with more reviews provide more reliable information to consumers.

[14] The long-run spatial dependence effect is given by $1/(1-\hat{\rho})$.

A very important debate in health economics concerns the link between competition intensity and price. Our results do not highlight a significant influence of our individual competition measure (ADISTANCE) on ophthalmologist prices except for Model 1. Surprisingly, the estimated coefficients are negative for all models, which is the opposite of expectation, as a higher distance should lead to a higher price (horizontal differentiation). According to us, this negative sign could reflect two main elements: the existence of noncompetitive behavior (with induced floor price) between Sector 2 physicians and/or the presence of a substitution between horizontal and vertical differentiation. The influence of our competition structure variable (SHARE S2) seems to indicate the existence of noncompetitive behavior. Indeed, our estimations clearly highlight a strong positive link between the share of Sector 2 in the neighborhood and ophthalmologist prices. This effect implies that for each percentage point increase in the share of Sector 2 in the neighborhood of a physician, price increases from nearly 0.03 euros (Model 1) up to 0.11 euros (Model 3) in the long run.[15]

Concerning the other variables, individual characteristics seem to have an effect. We detect a significant gender effect, as we estimate that on average, female ophthalmologists' prices are between 2.9 and 3.5 euros less than male prices. Physician activity being purely liberal also positively influences the price, but it is only significant for Model 2. City variables also matter. We estimate that the consultation price increases between 0.4 and 0.5 euros for every 1000 euros median income. Ophthalmologist prices are also positively related to the population density in all models. Finally, the coefficient associated with the inverse Mills ratio (selection bias) is negative and significant.

We now turn our analysis toward Sector 2 gynecologists who share some results with ophthalmologists. Indeed, we detect a significant positive spatial dependence among gynecologist prices. Given the value of this spatial dependence, between 40% and 45% of neighborhood prices is reflected in an increment of gynecologists' consultation price in the long run. The coefficient associated with the residual neighbors quality (λ) is also negative but not significant. This again highlights the fact that a positive spatial dependence reflects a reduction of price competition incentives in favor of imitative pricing. Concerning the effect of individual quality (RATING), we detect a significant positive influence except for Model 1 (which has the lowest RMSE), and the number of online reviews matters (C-RATING). Thus, it seems that vertical differentiation of gynecologists is significant and increases with the number of reviews received.

Concerning the link between competition intensity and price, we again find a negative relation between our individual competition measure (ADISTANCE) and price. This is again the opposite of what was expected, and for gynecologists, this relation is significant for both Model 1 and Model 2. This seems to again highlight the existence of noncompetitive behavior among Sector 2 gynecologists. Similar to ophthalmologists, the influence of our competition structure variable (SHARE S2) is significantly positive. This implies that the higher the

[15]The presence of endogenous term Wp implies that the marginal effect of any x is obtained as follows $\partial p/\partial x = \beta(I-\rho W)^{-1}$. To understand this result, consider a column vector $(N \times 1)$ of ones $\boldsymbol{\iota}$, with a W row-standardized and $|\rho| < 1$; the long-run spatial effect is given by:

$$\begin{aligned}(I-\rho W)^{-1}\boldsymbol{\iota} &= \left[I + \rho W + (\rho W)^2 + (\rho W)^3 + \cdots\right]\boldsymbol{\iota} = \left[I\boldsymbol{\iota} + \rho W\boldsymbol{\iota} + \rho^2 W(W\boldsymbol{\iota}) + \rho^3 WW(W\boldsymbol{\iota}) + \cdots\right],\\ &= \boldsymbol{\iota} + \rho\boldsymbol{\iota} + \rho^2\boldsymbol{\iota} + \rho^3\boldsymbol{\iota} + \cdots = (1/(1-\rho))\,\boldsymbol{\iota}.\end{aligned}$$

share of Sector 2 in the neighborhood is, the higher the price. This effect implies that for each percentage point increase in the share of Sector 2 in the neighborhood of a gynecologist, price increases from between 0.03 euros (Model 1) to 0.11 euros (Model 3).

For the other variables, individual characteristics seem to have an impact. Indeed, we estimate that on average, female gynecologists' prices are between 4.1 and 4.2 euros less than male prices. Physician activity being purely liberal also positively influences the price. City variables also matter. We estimate that price increases between 0.6 and 0.7 euros for every 1000 euros median income. Gynecologist prices are also positively related to the density of the population in all models. Finally, the coefficient associated with the inverse mills ratio (selection bias) is negative and significant.

We complete the analysis of Table 2 results by focusing on our pediatrician sample. Even if some results are common with the two other specializations, important differences seem to exist, especially regarding the influence of competition. Indeed, contrary to the case with ophthalmologists and gynecologists, the influence of our individual competition variable (ADISTANCE) has the expected positive sign. It thus highlights that, contrary to the two other types of specialists, horizontal differentiation plays a role for pediatricians. It also implies that potential noncompetitive behavior is less important for this specialty compared to the two others. We cannot completely rule out the existence of noncompetitive behavior between Sector 2 pediatricians, as the effect of the competition structure variable (SHARE S2) is stronger than that of the two other types of specialists. Indeed, for each percentage point increase in the share of Sector 2 in the neighborhood of a pediatrician, price increases from 0.07 euros (Model 1) to 0.18 euros (Model 3). Another difference concerns the influence of individual consultation quality. Indeed, contrary to the two other specialists, both the average rating and the number of reviews received do not seem to influence pediatricians' prices.

We also detected important spatial effects for pediatricians. Indeed, there exists a strong positive spatial dependence between pediatrician prices regardless of the definition of the local neighborhood. The spatial lag coefficient is estimated to be between 0.371 (Model 3) and 0.391 (Model 1), indicating that between 59% and 64% of neighborhood prices are reflected in an increment of pediatricians' consultation prices. The importance of the spatial effect on pediatricians' prices is also highlighted by the significant negative coefficient associated with neighbors' consultation quality ($\overline{\text{RATING}}$). For ophthalmologists, the higher the neighboring quality of a physician is, the lower its price. Nevertheless, due to high positive spatial dependence, this effect seems to be limited.

For the other variables, individual characteristics seem to matter. Indeed, we estimate that, on average, the female ophthalmologist price is between 2.9 and 3.4 euros less than the male price. Contrary to the other specializations, the fact that physician activity is purely liberal negatively influences the price. This specificity for pediatricians can be explained by a lower share of pediatricians who only work in their own office (see Table 1).

Concerning city variables, only median income seems to influence pediatricians' prices. We estimate that price increases between 0.3 and 0.4 euros for every 1000 euros median income. Pediatrician prices are not influenced by the population density in any of the models. Finally, the coefficient associated with the inverse mills ratio (selection bias) is negative but insignificant, suggesting that for this specialty, our selected sample does not suffer from a significant selection bias.

Overall, our empirical findings show that the circular-city framework used to analyze free-billing physicians in France is adequate. Looking at $RMSE$, Model 1 or Model 2 always better fit the data compared to Model 3, which also indicates that the best empirical definitions of the local market do not exceed a two-step distance. This is in line with circular-city models (see Alderighi and Piga, 2012). All our estimations, regardless of the specialty studied, estimate a positive ρ for equation (8). In line with our theoretical model, this means that the consultation's quality reduces price competition incentives in the market. The estimated value of ρ for all specializations also implies important local imitative pricing.

From an econometric perspective, it also implies that ignoring the existence of this positive spatial dependence in price will lead OLS to provide bias estimates of the marginal effect of covariates (including competition and quality measures) with inconsistent standard errors. As shown in Franzese and Hays (2007) or Rüttenauer (2019), the sign and strength of the bias for a particular variable x depends both on the sign and value of ρ as well as the linear link between x and Wy. Concerning the effect of competition intensity on price, our results differ from recent empirical evidence in France for two specializations (ophthalmologists and pediatricians); see Choné et al., 2019. Indeed, for those specializations, we detect a significant positive relationship between competition intensity and price, suggesting the presence of collusion behavior. The natural explanation of the difference with Choné et al. (2019) is that they did not control for spatial dependence. Indeed, using our data and a competition variable similar to that in Choné et al. (2019), i.e., the density of physicians (x) at the city level, we obtain a positive correlation between x and Wy. As we detect a positive spatial dependence, it means that OLS upward biases the estimated effect of competition ($\hat{\beta}_{OLS} = \beta + \rho Cov(x, Wy)/V(x)$). This explains why we find opposite results.

	Ophthalmologists			Gynecologists			Pediatricians		
Models	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GENDER	-2.191^{***}	-1.760^{***}	-2.087^{***}	-2.969^{***}	-2.942^{***}	-2.835^{***}	-1.809^{***}	-2.109^{***}	-1.813^{***}
	(0.336)	(0.275)	(0.293)	(0.351)	(0.283)	(0.189)	(0.569)	(0.464)	(0.493)
LIBERAL	0.398	0.447^{*}	0.574	1.024^{***}	0.849^{**}	0.800^{**}	-2.481^{***}	-2.724^{***}	-2.641^{***}
	(0.398)	(0.248)	(0.365)	(0.364)	(0.384)	(0.322)	(0.549)	(0.578)	(0.571)
MEDIAN	0.349^{***}	0.272^{***}	0.258^{***}	0.479^{***}	0.403^{***}	0.458^{***}	0.235^{***}	0.241^{***}	0.199^{***}
	(0.052)	(0.045)	(0.049)	(0.055)	(0.057)	(0.054)	(0.070)	(0.064)	(0.065)
POPD	0.232^{***}	0.174^{***}	0.130^{**}	0.198^{***}	0.134^{**}	0.122^{**}	0.014	−0.005	−0.042
	(0.059)	(0.050)	(0.055)	(0.067)	(0.067)	(0.060)	(0.060)	(0.064)	(0.066)
ADISTANCE	-0.030^{**}	−0.009	−0.007	-0.052^{***}	-0.027^{**}	−0.006	0.043^{**}	0.023^{**}	0.016^{*}
	(0.013)	(0.008)	(0.007)	(0.017)	(0.012)	(0.008)	(0.019)	(0.011)	(0.009)
SHARE S2	1.857^{***}	5.526^{***}	6.691^{***}	2.381^{***}	6.472^{***}	7.441^{***}	4.361^{***}	8.079^{***}	11.378^{***}
	(0.559)	(0.522)	(1.100)	(0.707)	(1.162)	(1.215)	(1.319)	(1.396)	(2.020)
RATING	−0.164	0.076	0.026	0.139	0.310^{**}	0.273^{**}	−0.212	−0.058	−0.003
	(0.137)	(0.140)	(0.119)	(0.136)	(0.136)	(0.129)	(0.282)	(0.277)	(0.277)
C-RATING	0.036^{***}	0.043^{***}	0.033^{***}	0.051^{***}	0.062^{***}	0.058^{***}	0.031	0.025	0.020
	(0.013)	(0.011)	(0.012)	(0.010)	(0.014)	(0.013)	(0.041)	(0.041)	(0.041)
IMR	-2.540^{***}	-2.829^{***}	-2.539^{***}	-1.721^{**}	-1.146^{*}	-1.690^{**}	−1.616	−1.174	−1.136
	(0.508)	(0.591)	(0.432)	(0.682)	(0.678)	(0.718)	(1.374)	(1.116)	(1.342)
$\overline{\text{RATING}}$	-0.465^{***}	-0.383^{***}	-0.427^{***}	−0.028	−0.096	−0.021	-0.322^{**}	-0.302^{**}	-0.366^{**}
	(0.109)	(0.114)	(0.115)	(0.133)	(0.153)	(0.141)	(0.147)	(0.143)	(0.143)
$W \times$ PRICE	0.329^{***}	0.388^{***}	0.396^{***}	0.291^{***}	0.307^{***}	0.307^{***}	0.391^{***}	0.380^{***}	0.371^{***}
	(0.029)	(0.017)	(0.016)	(0.032)	(0.036)	(0.042)	(0.049)	(0.044)	(0.044)
N	1674	1674	1674	1862	1862	1862	596	596	596
$RMSE$	10.605	10.542	10.554	10.898	10.844	10.855	8.980	8.984	8.996

Note: Constant terms are omitted. Standard errors in parentheses. GMM estimation with robust het s.e. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Estimation of the Spatial Lag Models using City/District Fixed Effects.

6.2 Investigating a potential substitution between vertical and horizontal differentiation

In this subsection, we try to investigate whether the unexpected sign we obtain for some specializations with respect to our main competition variable (ADISTANCE) could be partially explained by a link existing between vertical (quality) and horizontal (space) differentiation. To do so, we include in our models an interaction effect between our quality measure (RATING) and our average distance measure (ADISTANCE). Our results are presented in Table 3. The introduction of this interaction effect changes the sign of our distance measure for ophthalmologists and gynecologists, which becomes positive regardless of the definition of the local market, as theoretically expected. For pediatricians, the coefficient remains positive and statistically significant but strongly increases in terms of value. This interaction effect also changes the sign of the coefficient related to individual consultation quality for ophthalmologists and pediatricians, which becomes positive regardless of the definition of the local market. For gynecologists, the coefficient remains positive but increases in value. Finally, the coefficient related to this cross-variable is always negative for all specializations regardless of the specialization and the definition of the local market. Even if this coefficient is statistically significant for ophthalmologists and pediatricians only, it seems to indicate that a substitution effect is at stake between vertical and horizontal differentiation, which could partially explain the unexpected coefficient for (ADISTANCE) in Table 2. The intuition behind this result is easy to understand. When the local market competition intensity is stronger, it gives more incentive to physicians to escape price competition by increasing their quality differentiation, whereas in the local market for which competition intensity is low, quality is not necessary to have relative monopoly power. These results concerning the existence of a substitution effect between vertical and horizontal differentiation seem to be robust, as all other covariates (including the spatial lag coefficient) have comparable value signs and significance when compared to Table 2.

Consequently, it seems that physicians' pricing decisions are driven by highly imitative pricing (high ρ value), noncompetitive behavior (strong effect of SHARE S2 and limited for ADISTANCE) and substitution between horizontal and vertical differentiation.

	Ophthalmologists			Gynecologists			Pediatricians		
Models	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Gender	-2.070^{***}	-1.742^{***}	-1.843^{***}	-3.018^{***}	-3.026^{***}	-2.933^{***}	-1.595^{***}	-1.989^{***}	-1.568^{***}
	(0.346)	(0.265)	(0.324)	(0.353)	(0.290)	(0.218)	(0.561)	(0.438)	(0.488)
liberal	0.421	0.157	0.504	1.003^{***}	0.783^{*}	0.721^{**}	-2.439^{***}	-2.596^{***}	-2.638^{***}
	(0.367)	(0.249)	(0.358)	(0.373)	(0.401)	(0.359)	(0.510)	(0.561)	(0.545)
median	0.334^{***}	0.270^{***}	0.255^{***}	0.467^{***}	0.404^{***}	0.462^{***}	0.232^{***}	0.236^{***}	0.189^{***}
	(0.052)	(0.046)	(0.052)	(0.055)	(0.058)	(0.054)	(0.066)	(0.063)	(0.066)
Dpop	0.213^{***}	0.204^{***}	0.149^{**}	0.192^{***}	0.131^{*}	0.115^{*}	-0.001	-0.012	-0.041
	(0.058)	(0.053)	(0.058)	(0.068)	(0.070)	(0.066)	(0.055)	(0.063)	(0.069)
Adistance	0.039	0.053^{**}	0.050^{**}	0.016	0.009	0.015	0.303^{***}	0.115^{**}	0.100^{***}
	(0.037)	(0.022)	(0.020)	(0.046)	(0.031)	(0.021)	(0.083)	(0.045)	(0.027)
Share S2	1.926^{***}	5.592^{***}	6.948^{***}	2.396^{***}	6.286^{***}	7.209^{***}	4.704^{***}	8.463^{***}	11.589^{***}
	(0.571)	(0.534)	(1.211)	(0.701)	(1.186)	(1.245)	(1.252)	(1.265)	(1.845)
Rating	0.099	0.343	0.484^{**}	0.190	0.374^{*}	0.368^{*}	0.193	0.267	0.499
	(0.231)	(0.222)	(0.239)	(0.180)	(0.210)	(0.212)	(0.341)	(0.359)	(0.385)
C-rating	0.036^{***}	0.044^{***}	0.035^{***}	0.045^{***}	0.059^{***}	0.056^{***}	0.026	0.023	0.015
	(0.013)	(0.011)	(0.012)	(0.011)	(0.013)	(0.012)	(0.040)	(0.041)	(0.042)
rating × Adistance	-0.019^{*}	-0.018^{***}	-0.016^{***}	-0.019	-0.009	-0.006	-0.063^{***}	-0.021^{*}	-0.019^{***}
	(0.011)	(0.007)	(0.006)	(0.012)	(0.008)	(0.005)	(0.022)	(0.012)	(0.007)
IMR	-3.065^{***}	-3.017^{***}	-2.890^{***}	-1.631^{**}	-1.008	-1.631^{**}	-1.785	-1.055	-0.748
	(0.572)	(0.671)	(0.686)	(0.694)	(0.684)	(0.716)	(1.345)	(0.933)	(1.267)
$\overline{\text{rating}}$	-0.509^{***}	-0.398^{***}	-0.477^{***}	-0.033	-0.105	-0.034	-0.360^{**}	-0.318^{**}	-0.329^{**}
	(0.104)	(0.108)	(0.109)	(0.131)	(0.159)	(0.150)	(0.141)	(0.139)	(0.140)
$W\times$Price	0.349^{***}	0.359^{***}	0.396^{***}	0.297^{***}	0.311^{***}	0.312^{***}	0.380^{***}	0.387^{***}	0.367^{***}
	(0.028)	(0.018)	(0.026)	(0.033)	(0.037)	(0.042)	(0.042)	(0.042)	(0.043)
N	570	570	570	726	726	726	310	310	310
$RMSE$	10.630	10.508	10.546	10.908	10.867	10.858	8.961	8.980	8.985

Note: Constant terms are omitted. Standard errors in parentheses. GMM estimation with robust het s.e. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Estimation of Models with link between vertical and horizontal differentiation

6.3 Investigating heterogeneous imitative pricing

In this section, our aim is to test an important implication related to proposition 2 of our theoretical model. Indeed, corollary 2 establishes that differences in physician density should lead to significant differences in the level of imitative pricing measured by ρ. We thus decide to estimate a structural break version of Model (8):

$$p = \rho_0 Wp + \rho_1 WpD + XB + \phi q + \lambda \overline{q} + \varepsilon, \tag{13}$$

where D represents a binary variable that takes the value 1 when the physician operates in a city with a high physician density and zero otherwise. The ρ_1 coefficient captures the additional imitative pricing in high-density cities. For our three specializations, physician density at the city level is strongly positively skewed. Indeed, the mean physician density is higher than the third quartile (Q3 hereafter) for ophthalmologists and gynecologists. We thus decide to choose Q3 as our threshold. Consequently, the results presented in Table 4 estimate the change in the ρ value for physicians operating in cities with the 25% highest physician density with respect to the average ρ value for the other physicians, that is, those operating in cities with the 75% lowest physician density.[16]

The results presented in Table 4 are very similar to those presented in Table 2 concerning the impact of all covariates. Consequently, we focus our discussion on the estimated value of imitative pricing (ρ) between physicians located in cities with the 25% highest density and the others. The results highlight strong differences except for pediatricians Model 1, but the best specification in terms of RMSE for all specializations is Model 2. For all specializations, the imitative pricing coefficient (ρ) is at least two times higher for physicians located in cities with the 25% highest density compared to the rest of physicians. Indeed, if we take Model 2 as our preferred specification, the estimated ρ value for ophthalmologists in the fourth quartile in terms of physician density is 0.517 ($\widehat{\rho_0} + \widehat{\rho_1} = 0.246 + 0.271$) compared to 0.246 for the other physicians. For gynecologists, the difference is even higher, with an estimated ρ value for the fourth quartile of 0.738 compared to 0.223 for the others. Finally, the estimated ρ value for pediatricians in the fourth quartile in terms of physician density is 0.513 compared to 0.157 for the others. All these results clearly highlight a significant link between physician density and the importance of imitative pricing and validate corollary 2 results.

[16] We are aware that a complete test of corollary 2 could only be realized with a panel dataset allowing us to test heterogeneous ρ for each city. Nevertheless, even if our test is less general, it allows us to highlight the existence of heterogeneity in imitative pricing with respect to physician density.

	Ophthalmologists			Gynecologists			Pediatricians		
Models	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Gender	-1.783^{***}	-1.926^{***}	-1.944^{***}	-2.721^{***}	-2.896^{***}	-2.994^{***}	-1.910^{***}	-1.460^{**}	-1.154^{*}
	(0.326)	(0.290)	(0.317)	(0.290)	(0.244)	(0.203)	(0.579)	(0.581)	(0.595)
liberal	0.273	0.169	0.411	0.945^{***}	1.082^{***}	0.682^{**}	-2.439^{**}	-2.708^{***}	-2.423^{***}
	(0.379)	(0.288)	(0.339)	(0.324)	(0.343)	(0.286)	(0.550)	(0.556)	(0.517)
median	0.368^{***}	0.324^{***}	0.285^{***}	0.433^{***}	0.411^{***}	0.430^{***}	0.198^{***}	0.088	0.064
	(0.054)	(0.046)	(0.052)	(0.047)	(0.050)	(0.051)	(0.074)	(0.082)	(0.080)
Dpop	0.267^{***}	0.251^{***}	0.203^{***}	0.280^{***}	0.208^{***}	0.155^{***}	0.047	0.052	0.063
	(0.059)	(0.059)	(0.055)	(0.070)	(0.049)	(0.059)	(0.061)	(0.064)	(0.060)
Adistance	-0.013	-0.011	-0.003	-0.052^{***}	-0.027^{**}	-0.013^{*}	0.050^{**}	0.020	0.015
	(0.013)	(0.007)	(0.007)	(0.013)	(0.010)	(0.008)	(0.021)	(0.013)	(0.011)
Share S2	2.685^{***}	5.635^{***}	6.353^{***}	3.106^{***}	5.984^{***}	8.427^{***}	4.216^{***}	11.591^{***}	14.011^{***}
	(0.582)	(0.575)	(1.142)	(0.658)	(1.109)	(1.205)	(1.377)	(1.803)	(2.382)
Rating	-0.269	-0.059	-0.185	0.116	0.216	0.309^{**}	-0.153	0.016	0.087
	(0.174)	(0.162)	(0.168)	(0.139)	(0.140)	(0.132)	(0.295)	(0.289)	(0.288)
C-rating	0.040^{***}	0.042^{***}	0.031^{***}	0.046^{***}	0.055^{***}	0.048^{***}	0.017	-0.024	-0.022
	(0.012)	(0.010)	(0.011)	(0.013)	(0.011)	(0.010)	(0.042)	(0.044)	(0.044)
IMR	-2.959^{***}	-1.742^{***}	-2.906^{***}	-1.424^{*}	-1.248	-1.688^{**}	-1.922	-1.071	-1.184
	(0.760)	(0.581)	(0.784)	(0.832)	(0.793)	(0.723)	(1.416)	(1.194)	(1.449)
$\overline{\text{rating}}$	-0.411^{***}	-0.408^{***}	-0.424^{***}	-0.003	-0.052	0.103	-0.317^{*}	-0.159	-0.229
	(0.127)	(0.099)	(0.123)	(0.135)	(0.146)	(0.121)	(0.165)	(0.172)	(0.172)
$W\times$Price	0.230^{***}	0.246^{***}	0.288^{***}	0.206^{***}	0.223^{***}	0.198^{***}	0.357^{***}	0.157^{**}	0.131^{**}
	(0.033)	(0.033)	(0.029)	(0.027)	(0.032)	(0.033)	(0.062)	(0.070)	(0.065)
$W\times(\text{Price}\times D)$	0.430^{***}	0.271^{***}	0.355^{***}	0.515^{***}	0.515^{***}	0.592^{***}	0.089	0.356^{***}	0.420^{***}
	(0.062)	(0.034)	(0.067)	(0.151)	(0.160)	(0.140)	(0.138)	(0.132)	(0.139)
N	570	570	570	726	726	726	310	310	310
$RMSE$	10.667	10.506	10.604	10.967	10.945	10.948	8.963	8.901	8.906

Note: Constant terms are omitted. Standard errors in parentheses. GMM estimation with robust het s.e. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Estimation of Models with heterogeneous spatial effect

6.4 Robustness check

The empirical results presented before could lead to important implications for health policy. To validate the solidity of our results and, in particular, the existence of important imitative pricing in physicians' price and potential noncompetitive behavior, we implement a number of robustness checks. In this subsection, we only describe the results that we obtain and put the estimation tables in the appendices.

France as a single market

In Appendix C, we present the results obtained when we do not define a specific local market for each physician but instead allow the possibility of a link between all physicians. We, thus, use the spatial matrix (W_{exp}, see section 5.1) that links all physicians in France. We then weight the link using the exponential distance measure. A short comparison of Table C.1 with Table 2 shows that all results previously obtained still hold if we do not define a specific local neighborhood for each physician, reinforcing our confidence with our results presented in previous Tables.

The use of different dummies to control for location bias

An important element to control for is the location choice of physicians. As we work on cross-sectional data, the best we can do is to use city dummies. Nevertheless, as described previously, we cannot include city dummies for each city, as in some of them, only one physician operates. In Appendix D, we show estimation results obtained using NUTS3 fixed effects for each specialty. To summarize, when we control less for location bias, the spatial lag coefficient is relatively similar for pediatricians, higher for gynecologists and lower for ophthalmologists but remains strongly significant for all specializations. For the other covariates, we obtain similar values compared to previous Tables.

Testing another measure of competition intensity

An important complexity when we use spatial models is to define an appropriate measure of competition. In this paper, we try to be as close as possible to the theoretical model measure (i.e., distance between physicians) by introducing an individual distance measure. Nevertheless, in the main model, we include two distinct measures. The first measures the average distance between a physician and its r-th degree neighbors (including both S1 and S2 physicians), and the second measures the proportion of S2 physicians in this neighborhood. To confirm that our results concerning the existence of potential noncompetitive behavior among Sector 2 physicians are not related to those particular measures, we use another competition variable in this section that combines the two presented in our main results. Basically, we recompute the variable ADISTANCE but only on Sector 2 physicians. This new variable called ADISTANCE - S2 in Table E.1 presented in Appendix E is the average distance between a Sector 2 physician and its r-th degree Sector 2 neighboring physicians. In Table E.1, we see that the coefficient related to our new competition measure is negative for all specializations regardless of the definition of the local market and only statistically significant for ophthalmologists and gynecologists.

This is in line with the noncompetitive behavior reported before. Indeed, in our core result, we highlight a negative coefficient related to ADISTANCE for ophthalmologists and gynecologists, whereas it was positive for pediatricians. We also found a significant positive effect of the share of free-billing physicians on price for all specializations. The new results presented in this table confirm significant noncompetitive behavior among ophthalmologists and gynecologists, whereas this does not seem to be the case for pediatricians.

6.5 Estimating the importance of imitative pricing in the long run using simulations

The interpretation of the spatial effects is a prime interest in spatial econometrics, and there is a wide literature on how evaluating these effects; see Kim et al. (2003); Le Gallo et al. (2003); Hondroyiannis et al. (2009); LeSage and Pace (2009); Arbia et al. (2020), among others.

The objective of this section is to use the estimated spatial dependence between physician prices to simulate the impact of a change in one physician price on the other physicians' price. For this purpose, we follow the approach developed by Le Gallo et al. (2003), where the influence of spatial spillovers is generated through shocks in the error terms. For simplicity in this section, we apply this method using empirical Model 2, which defines the first- and second-order contiguity neighbors as the local market for a physician. Note that we can rewrite Model 2 in the following reduced form:

$$p = (I - \rho W_{12})^{-1} \left[XB + \phi q + \lambda \overline{q}_{12}\right] + (I - \rho W_{12})^{-1} \varepsilon. \tag{14}$$

Instead of measuring the spatial effects using the traditional marginal effect of a change in one explanatory variable, this reduced form allows us to estimate the spatial impact or the diffusion (emission) effect given a random shock in the error term. It will allow us to evaluate the spatial contagion of a shock affecting one physician to all other physicians. The mechanism of diffusion is through inverse spatial transformation $(I - \rho W_{12})^{-1}$. The magnitude of these effects is influenced by the location of each physician in the spatial matrix W and by the spatial dependence effect through the estimated ρ parameter.

We evaluate the average impact of a shock δ affecting a physician i's price. To obtain a distribution of emission effects on other physicians, we need to evaluate an independent and sequential shock for all physicians. To illustrate this, we simulate a shock δ equal to ten percent of the average price in France. Formally, our simulation experiment can be described as follows. Let $\widehat{\boldsymbol{\varepsilon}}_i$ be a $N \times 1$ vector containing the estimated errors of Model 2 with a shock affecting physician i:

$$\widehat{\boldsymbol{\varepsilon}}_i' = \begin{pmatrix} \widehat{\varepsilon}_1 & \cdots & \widehat{\varepsilon}_i + \delta & \cdots & \widehat{\varepsilon}_N \end{pmatrix}'. \tag{15}$$

Therefore, the $(N \times 1)$ vector p_i^* of simulated prices after a shock in the error term of physician i can be computed as followed:

$$
\begin{aligned}
p_i^* &= (I - \widehat{\rho} W_{12})^{-1} \left[X\widehat{B} + \widehat{\phi} q + \widehat{\lambda} \overline{q}_{12} \right] + (I - \widehat{\rho} W_{12})^{-1} \widehat{\varepsilon}_i, \\
&= A^{-1}\mathbf{X} + A^{-1}\widehat{\boldsymbol{\varepsilon}}_i
\end{aligned}
\tag{16}
$$

where $\widehat{\rho}$, $\widehat{B}$, $\widehat{\phi}$ and $\widehat{\lambda}$ are the GMM estimations of ρ, B, ϕ and λ. $A = (I - \widehat{\rho} W_{12})$ and $\mathbf{X} = \left[X\widehat{B} + \widehat{\phi} q + \widehat{\lambda} \overline{q}_{12} \right]$.

If there is an independent and sequential shock for each physician in the sample, then P^* represents the matrix of dimension $(N \times N)$ that contains the observations on the simulated prices as follows:

$$
P^* = \begin{bmatrix} p_1^* & \cdots & p_N^* \end{bmatrix} = A^{-1} \begin{bmatrix} \mathbf{X} & \cdots & \mathbf{X} \end{bmatrix} + A^{-1} \begin{bmatrix} \widehat{\boldsymbol{\varepsilon}}_1 & \cdots & \widehat{\boldsymbol{\varepsilon}}_N \end{bmatrix}. \tag{17}
$$

This expression can be written as follows:

$$
P^* = \boldsymbol{\iota}' \otimes A^{-1}\mathbf{X} + A^{-1}\widehat{\boldsymbol{\Upsilon}}, \tag{18}
$$

where $\boldsymbol{\iota}'$ is a $(1 \times N)$ vector of ones, $\otimes$ is the Kronecker product, and $\widehat{\boldsymbol{\Upsilon}}$ is the matrix of dimension $(N \times N)$ defined as $\widehat{\boldsymbol{\Upsilon}} = \begin{bmatrix} \widehat{\boldsymbol{\varepsilon}}_1 & \cdots & \widehat{\boldsymbol{\varepsilon}}_N \end{bmatrix}$. Since each element $\widehat{\boldsymbol{\varepsilon}}_i$ is defined following equation (15), this matrix $\widehat{\boldsymbol{\Upsilon}}$ can also be written as:

$$
\widehat{\boldsymbol{\Upsilon}} = \begin{bmatrix} \widehat{\varepsilon}_1 + \delta & \widehat{\varepsilon}_1 & \cdots & \widehat{\varepsilon}_1 \\ \widehat{\varepsilon}_2 & \widehat{\varepsilon}_2 + \delta & \cdots & \widehat{\varepsilon}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{\varepsilon}_N & \widehat{\varepsilon}_N & \cdots & \widehat{\varepsilon}_N + \delta \end{bmatrix} = \boldsymbol{\iota}' \otimes \widehat{\boldsymbol{\varepsilon}} + \delta I,
$$

where δ is the introduced shock.

The expression (18) yields a matrix of dimensions $(N \times N)$, where column i indicates the simulated price for all physicians in the sample after a shock in physician i. Each column i gives information on the emission effect of the spatial diffusion process from a specific physician i to all the other physicians.

To provide meaningful results, we also apply this method using empirical Model 2 with heterogeneous spatial dependence (see Table 4), which can be rewritten in the following reduced form:

- Model for physicians in a city with a weak density level $(D = 0)$:

$$
p = (I - \rho_0 W_{12})^{-1} \left[XB + \phi q + \lambda \overline{q}_{12} \right] + (I - \rho_0 W_{12})^{-1} \varepsilon. \tag{19}
$$

- Model for physicians in a city with a strong density level ($D = 1$):

$$p = (I - (\rho_0 + \rho_1)W_{12})^{-1} [XB + \phi q + \lambda \overline{q}_{12}] + (I - (\rho_0 + \rho_1)W_{12})^{-1} \varepsilon. \tag{20}$$

Figure 5 displays the simulation results (emission effects) obtained using estimated Model 2 with homogeneous (see Table 2) and heterogeneous (see Table 4) spatial dependence (SD hereafter). These effects should be considered long-run effects after spatial diffusion reaches a stationary value at the price of each physician.

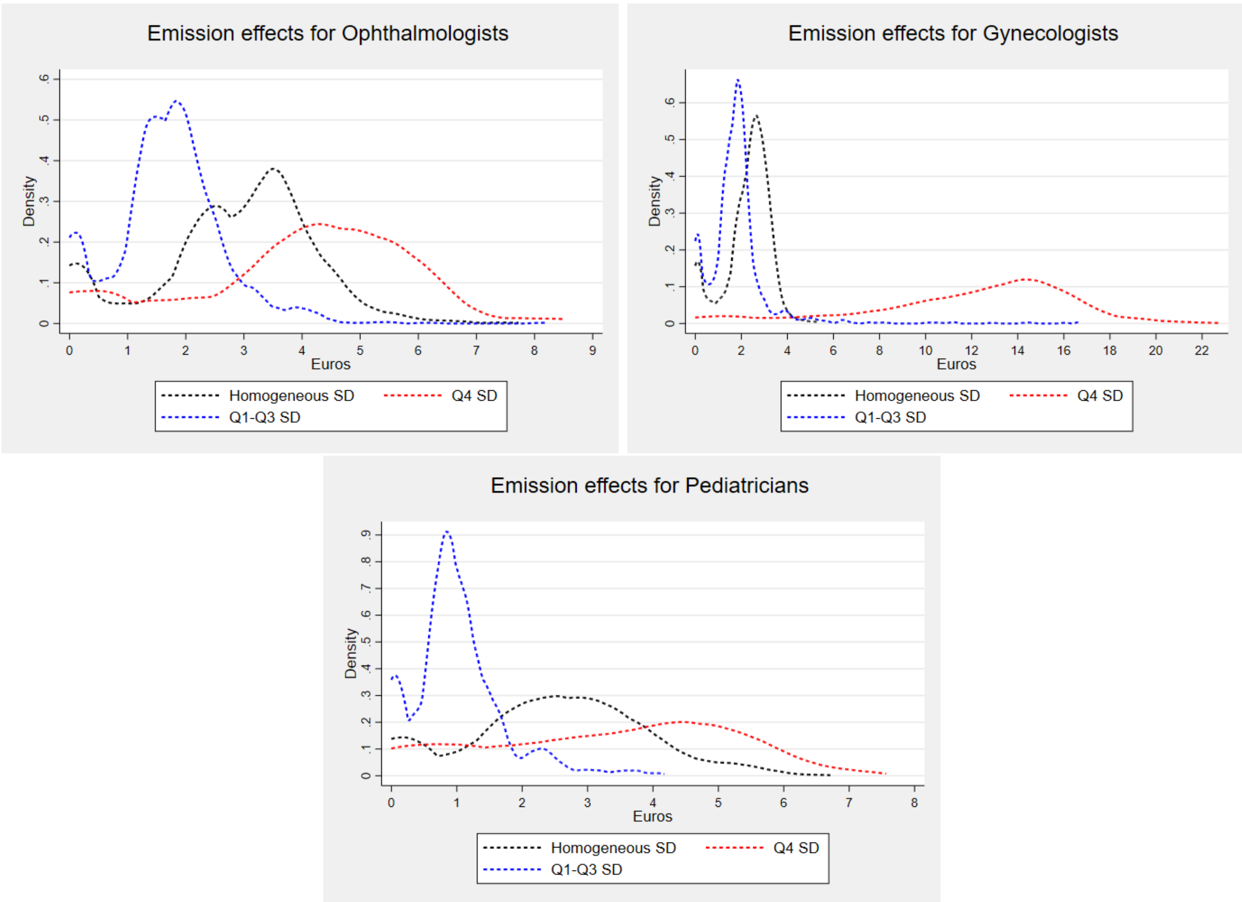

Figure 5: Simulated spatial effects.

Concerning simulations on ophthalmologists, we estimate an average emission effect of 2.84 euros when SD is homogeneous, representing approximately 57% of the simulated price increase (10% of the average price or 4.95 euros). Otherwise, if an ophthalmologist in France increases the price by 4.95 euros, this will generate a cumulative increase in the price of all other physicians of 2.84 euros. When we consider heterogeneous SD, we estimate an average emission effect of 1.69 euros for those operating in the 75% cities with the lowest ophthalmologist density, whereas this effect increases to 3.91 euros for those operating in the 25% of cities with the highest ophthalmologist density.

Regarding gynecologists, the average emission effect of a physician is estimated at 2.29 euros when SD is homogeneous, representing 41% of the price increase (10% of the average price or 5.54 euros). When we consider heterogeneous SD, we estimate an average emission effect of 1.80 euros for those operating in the 75% cities with the lowest gynecologist density, whereas this effect surges to 11.80 euros for those operating in the 25% cities with the highest gynecologist density.

Finally, in the case of pediatricians, the average emission effect of a physician is estimated at 2.46 euros when SD is homogeneous, which represents 54% of the price increase (10% of the average price or 4.51 euros). When we consider heterogeneous SD, we estimate an average emission effect of 1.00 euros for those operating in the 75% of cities with the lowest gynecologist density, whereas this effect increases to 3.17 euros for those operating in the 25% of cities with the highest gynecologist density.

All these simulations highlight an important diffusion effect of an individual price increase to other physicians; thus, it provides an empirical idea of the importance of the imitative pricing (positive spatial dependence) among physicians.

6.6 A brief policy discussion to limit physicians' additional fees

The empirical evidence provided in this paper has several implications for policy-makers, especially in France. Since 2013, the French government has implemented an important reform to try to stop the progression of additional fees (which increased from 0.9 billion in 1990 to reach 2.66 billion euros in 2016 (CNAMTS, 2017)). To summarize quickly, the government and the NHI entered negotiations with physician unions to create an intermediate Sector - "Contract to improve access to health care" ("Contrat d'accès aux soins" in French, or CAS) - between Sectors 1 and 2. Since 2013, free-billing (Sector 2) physicians have been free to sign up for this contract or not; those who sign commit to setting their fees at a level of not more than 100% of the regulated fee. In return, these physicians receive several benefits while their patients are able to obtain higher reimbursements from both the NHI and private health insurance. The CAS is signed annually and is renewable, and after each annual period, it can be discontinued by the physician who then would return to Sector 2. This contract was slightly modified in 2017 and renamed "Practice Price Control Option" ("Option Pratique Tarifaire Maitrisée" in French, or OPTAM).

The latest available document from CNAM (2018) showed that nearly 50% of physicians under free-billing contracts signed the new OPTAM contract as of September 2018. While this may be seen as very positive, and unsurprising, at first glance, it raises questions on the effectiveness of this new contract to truly address the problem as a whole. Indeed, our price data on three physician specializations for 2013 show that the median price is lower than twice the regulated fee (which is the maximum price under OPTAM). This observation is confirmed by the paper of Choné et al. (2019) that uses 2014 price data. Consequently, if an adoption rate of 50% for the OPTAM contract is an important step to improve patients' access to healthcare in France (due to better coverage from NHI and private health insurance), it also raises questions on 1) the windfall effects for physicians who accepted the new contract, 2) the increasing portion of additional fees paid by the NHI, 3) the price increases of private insurance due to higher coverage and, finally, 4) the remaining 50% pure free-billing physicians.

Our empirical results highlight a significant imitative pricing that exists between neighboring free-billing physicians that seems to increase with physician density. One important consequence of this reality is that an individual decision regarding a price increase will spread to other physicians who will imitate this price increase. As many empirical facts tend to highlight an important spatial concentration of free-billing physicians in denser areas with higher income, the location freedom is probably an important barrier for controlling the continuing increase in additional fees. This question of the freedom of establishment is not a new topic for policy-makers in France and has been recently put back on the table by the Directorate General of the French Treasury (2019). The main argument justifying this questioning is the growing appearance of medical deserts in France. We think that our paper provides another determinant argument in favor of reassessing this freedom. Indeed, the risk is not only of medical deserts, but also access to care in large metropolitan areas for people with modest incomes. The new OPTAM contract that socializes the cost of additional fees in France even more is another argument that could enter into the debate on the location freedom of physicians.

7 Conclusion and avenues for future research

France is one of the most interesting places to conduct experiments on analyzing physicians' pricing behavior. This is one of the few OECD countries that allows a significant proportion of its physicians to balance bill their patients with complete location freedom. These freedoms raise the issue of unequal access to healthcare and have become a major political and social issue in France. Indeed, this not only affects complex medical procedures but also recurring health needs, such as a simple consultation. Some empirical facts are worrisome. For instance, in 2011, a CNAM study showed that nearly 90% of the gynecologists located in Paris and in the Côte-d'Azur were under free-billing systems with extra fees being considerably higher than 100% of the regulated fee. In a more recent study, the Direction de la Recherche, des Études, de l'Evaluation et des Statistiques (DRESS, 2020) points out that the percentage of free-billing physicians has increased steadily since 2005.

In this paper, we make several contributions that provide new evidence on free-billing physician pricing behavior. To achieve this, we developed an innovative structural framework that we test on a unique geolocalized database of private practitioners for three medical specializations in France (ophthalmology, gynecology and pediatrics). We model physicians' behavior using a circular city framework where consultation quality influences both patients' utility and physicians' cost. We highlight that consultation quality reduces price competition if the effect of quality on physicians' cost dominates its marginal effect on patients' utility. We also highlight that the ratio between the effect of neighborhood and individual quality on price is a measure of imitative pricing. Indeed, by rewriting the equilibrium price equation, we show that this ratio exactly corresponds to the coefficient linking a physician's price to neighbors' prices. Another important result is that local competition intensity strengthens the value of this coefficient; that is, it increases imitative pricing. Our framework also allows us to highlight that reinforcing competition in areas with already high physician density is more likely to lead to a higher average price.

The second main contribution is building a unique dataset of more than 4,000 free-billing French physicians to be able to structurally identify the core parameters of the model and test its main implications, using an appropriate econometric strategy. We geolocalized each physician and collected patient satisfaction ratings (as a proxy for consultation quality) and various local environment information at the city or district level. This allows us to build and test different local market areas and competition measures for each physician without being restricted by administrative boundaries or arbitrary thresholds, as in existing studies. We develop a two-step spatial econometric procedure allowing us to control for sample selection bias, unknown heteroskedasticity and unknown distribution of errors using a GMM estimator instead of an ML estimator. We also carried out a number of alternative estimations to validate the robustness of our empirical results.

The final main contribution of this paper is to provide evidence of free-billing physicians' pricing behavior in France. We find a significant positive spatial dependence between a physician price and its neighbors' prices for all specializations. In relation to the model, this seems to support the idea that neighboring quality reduces price competition and that important imitative pricing exists between neighboring physicians. Indeed, the spatial dependence in price is estimated to be between 0.3 and 0.4, implying that a significant part of the individual price reflects neighborhood prices. We also test the prediction of a positive link between competition intensity and imitative pricing by comparing results on physicians operating in cities with the 25% highest physician density with the rest of our sample. Our results confirm the model's prediction, as the estimated spatial dependence in price is significantly higher for physicians operating in cities with the 25% highest physician density for all specializations. We finally run simulations on the impact of an individual price increase on other physicians to better appreciate the consequences of imitative pricing. We highlight significant propagation effects regardless of the specialization.

Our results provide important insights to explain significant price differences across French territory. It also contributes to the debate on the most effective tools to reduce additional fees in a system, allowing individual pricing decisions and thus ensuring access to care for all. As discussed in the last section of this paper, political reforms aimed at stopping the rise of additional fees have only implemented tools based on a voluntary choice of free-billing physicians that, in reality, could not incentivize them all. The most effective tools in the French context seem to focus on the question of physicians' location freedom.

In terms of future research, our paper indicates numerous possible avenues. First, our results call for a deeper use of and access to physician data. Indeed, by accessing a panel dataset on physician prices, we could greatly improve the understanding of imitative pricing. Among other things, it would allow us to estimate our structural model at the level of the city or local neighborhood and, thus, be able to obtain a distribution of imitative pricing. In doing so, we would be able to more deeply test the link between physician density and imitative pricing while controlling for any individual structural effect, including physician quality and location choice. Second, more evaluation is needed of the government's decision to stop the progression of extra fees. This is particularly true concerning the new contract (CAS and latter OPTAM) that increases the socialization of extra fees but may also have generated important windfall effects and negative indirect effects (such as price increases in private insurance). Third, our results also point to the need for more research on the impact of gender on physician behavior. Indeed, we detect a significant difference between the pricing of males and females for all specializations. This difference is important, as it represents approximately 10% of the median price. Fourth, more research needs to be conducted on the use of online information provided by patients' ratings. Indeed, more work needs to be carried out to better understand the bias of such measures and how they can be useful for public authorities as an indicator of care quality. Finally, in a broader view, we think that the theoretical and empirical framework developed in this paper offers an interesting method to analyze the existence of local imitative pricing in other service sectors, where an important number of firms are competing under horizontal and vertical differentiation.

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Any subsequent errors or omissions are the responsibility of the authors alone.

Supplementary material

Appendix A: Proof of propositions

Proof of Proposition 1

The utility function of a representative consumer is given by:

$$u_i(x) = r - p_i + \alpha q_i - t d_i. \tag{1}$$

The demand facing physician i is thus:

$$D_i = lh + \frac{h}{2t}\left[p_{i+1} + p_{i-1} - 2p_i + \alpha(2q_i - q_{i+1} - q_{i-1})\right]. \tag{2}$$

The profit of physician i is given by:

$$\pi_i = (p_i + \overline{p} - c_i)D_i. \tag{3}$$

The First Order Condition (FOC) with respect to p_i is given by:

$$lh + \frac{h}{2t}\left[p_{i+1} + p_{i-1} - 4p_i + \alpha(2q_i - q_{i+1} - q_{i-1})\right] - \frac{h}{2t}2\overline{p} + \frac{h}{2t}2c_i = 0, \tag{4}$$

which can be simplified as:

$$2tl + \left[p_{i+1} + p_{i-1} - 4p_i + \alpha(2q_i - q_{i+1} - q_{i-1})\right] - 2\overline{p} + 2c_i = 0 \tag{5}$$

We can rewrite the last FOC (5) to obtain N FOCs:

$$p_{i+1} - \alpha q_{i+1} - (2-\sqrt{3})[p_i - \alpha q_i] = (2+\sqrt{3})\left(p_i - \alpha q_i - (2-\sqrt{3})[p_{i-1} - \alpha q_{i-1}]\right) + 2\alpha q_i - 2(tl - \overline{p}) - 2c_i, \tag{6}$$

for all i.

By multiplying both side by $(2+\sqrt{3})$, we obtain the following set of n FOCs:

$$(2+\sqrt{3})\left(p_i - \alpha q_i - (2-\sqrt{3})[p_{i-1} - \alpha q_{i-1}]\right) =$$
$$(2+\sqrt{3})\left[(2+\sqrt{3})\left(p_{i-1} - \alpha q_{i-1} - (2-\sqrt{3})[p_{i-2} - \alpha q_{i-2}]\right) + 2\alpha q_{i-1} - 2(tl - \overline{p}) - 2c_{i-1}\right],$$

$$(2+\sqrt{3})^2\left(p_{i-1} - \alpha q_{i-1} - (2-\sqrt{3})[p_{i-2} - \alpha q_{i-2}]\right) =$$
$$(2+\sqrt{3})^2\left[(2+\sqrt{3})\left(p_{i-2} - \alpha q_{i-2} - (2-\sqrt{3})[p_{i-3} - \alpha q_{i-3}]\right) + 2\alpha q_{i-2} - 2(tl - \overline{p}) - 2c_{i-2}\right],$$

and so on; the n-th FOC is:

$$
\begin{aligned}
&(2+\sqrt{3})^{n-1}\left(p_{i+2}-\alpha q_{i+2}-(2-\sqrt{3})[p_{i+1}-\alpha q_{i+1}\right) = \\
&(2+\sqrt{3})^{n-1}\left[(2+\sqrt{3})\left(p_{i+1}-\alpha q_{i+1}-(2-\sqrt{3})[p_i-\alpha q_i]\right)+2\alpha q_{i+1}-2(tl-\overline{p})-2c_{i+1}\right].
\end{aligned}
\tag{7}
$$

Summing up all n FOCs gives:

$$
\begin{aligned}
&p_{i+1}-\alpha q_{i+1}-(2-\sqrt{3})[p_i-\alpha q_i] = \\
&(2+\sqrt{3})^n\left(p_{i+1}-\alpha q_{i+1}-(2-\sqrt{3})[p_i-\alpha q_i]\right)+2\sum_{j=0}^{n-1}(2+\sqrt{3})^j[\alpha q_{i-j}-c_{i-j}]-2(tl-\overline{p})\sum_{j=0}^{n-1}(2+\sqrt{3})^j.
\end{aligned}
\tag{8}
$$

Thus,

$$
p_{i+1}-\alpha q_{i+1}=(2-\sqrt{3})[p_i-\alpha q_i]+\frac{2(tl-\overline{p})}{1+\sqrt{3}}+\frac{2}{(2+\sqrt{3})^n-1}\sum_{j=0}^{n-1}(2+\sqrt{3})^j[c_{i-j}-\alpha q_{i-j}].
\tag{9}
$$

Applying a similar manipulation, i.e, multiplication of $(2-\sqrt{3})$ on both sides of the equations, yields the following:

$$
\begin{aligned}
&(2-\sqrt{3})\,[p_i-\alpha q_i] = \\
&(2-\sqrt{3})\left((2-\sqrt{3})[p_{i-1}-\alpha q_{i-1}]+\frac{2(tl-\overline{p})}{1+\sqrt{3}}+\frac{2\alpha}{(2+\sqrt{3})^n-1}\sum_{j=0}^{n-1}(2+\sqrt{3})^j[c_{i-j-1}-\alpha q_{i-j-1}]\right),
\end{aligned}
\tag{10}
$$

and so on; the n-th FOC is:

$$
\begin{aligned}
&(2-\sqrt{3})^{n-1}\,[p_{i+2}-\alpha q_{i+2}] = \\
&(2-\sqrt{3})^{n-1}\left((2-\sqrt{3})[p_{i+1}-\alpha q_{i+1}]+\frac{2(tl-\overline{p})}{1+\sqrt{3}}+\frac{2}{(2+\sqrt{3})^n-1}\sum_{j=0}^{n-1}(2+\sqrt{3})^j[c_{i-j+1}-\alpha q_{i-j+1}]\right).
\end{aligned}
\tag{11}
$$

Again, we sum up the n equations to obtain the following solution:

$$
\begin{aligned}
&p_{i+1}-\alpha q_{i+1}=(2-\sqrt{3})^n\,[p_{i+1}-\alpha q_{i+1}] \\
&+\frac{2(tl-\overline{p})}{1+\sqrt{3}}\sum_{k=0}^{n-1}(2-\sqrt{3})^k+\frac{2}{(2+\sqrt{3})^n-1}\sum_{k=0}^{n-1}\sum_{j=0}^{n-1}(2-\sqrt{3})^k(2+\sqrt{3})^j[c_{i-j-1}-\alpha q_{i-j-k}],
\end{aligned}
\tag{12}
$$

from which the closed-form expression for physician i's equilibrium price is derived:

$$
p_i^*=tl-\overline{p}+\alpha q_i+\frac{2}{[(2+\sqrt{3})^n-1][1-(2-\sqrt{3})^n]}\sum_{k=0}^{n-1}\sum_{j=0}^{n-1}(2-\sqrt{3})^k(2+\sqrt{3})^j[c_{i-j-k-1}-\alpha q_{i-j-k-1}].
\tag{13}
$$

Note that the double-summation term iterates through all physicians' q_i and c_i along the circle (i.e., $i \in 0, 1, .., n-1$). Thus, we can reduce the double summation to a single summation form:

$$\frac{2}{[(2+\sqrt{3})^n - 1][1-(2-\sqrt{3})^n]} \sum_{k=0}^{n-1} \sum_{j=0}^{n-1} (2-\sqrt{3})^k (2+\sqrt{3})^j [c_{i-j-k-1} - \alpha q_{i-j-k-1}] \Leftrightarrow \sum_{d=0}^{n-1} b_d [c_{i-d} - \alpha q_{i-d}]. \quad (14)$$

Lin & Wu (2015) proposed a similar transformation and we refer the reader to the supplementary content of their paper. We obtain the following value for b_d:

$$b_d = \frac{(2+\sqrt{3})^d + (2+\sqrt{3})^{n-d}}{\sqrt{3}[(2+\sqrt{3})^n - 1]} > 0. \quad (15)$$

Thus, we have the following pricing rule for physicians:

$$p_i^* = tl - \overline{p} + \alpha q_i + \sum_{d=0}^{n-1} b_d [c_{i-d} - \alpha q_{i-d}]. \quad (16)$$

The equilibrium price is negatively impacted by the density of physicians. Price increases with the quality of the physician but decreases with the quality of neighboring physicians. Price increases with the individual cost but also with the cost of neighboring physicians. Note that b_d decreases with both n and d implying that 1) more competition reduces the impact of cost but increase the impact of quality on physician price and 2) the higher the distance between two physicians, the lower their mutual impact.

Proof of Proposition 3

Using equilibrium price given by (6) in the paper, we can write:

$$q_i = \frac{[P_i^* - C)] - \eta \sum_{d=1}^{n-1} b_d q_{i-d}}{\theta}, \quad (17)$$

where $C = tl - \overline{p} + \delta h + \varepsilon$. Consequently for the $i - dth$ physician, we have:

$$q_{i-d} = \frac{[P_{i-d}^* - C)] - \eta \sum_{j=1}^{n-1} b_j q_{(i-d)-j}}{\theta}. \quad (18)$$

Inserting this last expression into P_i^* given by (6) in the paper, we obtain:

$$P_i^* = C + \theta q_i + \eta \sum_{d=1}^{n-1} b_d \left[\frac{[P_{i-d}^* - C] - \eta \sum_{j=1}^{n-1} b_j q_{(i-d)-j}}{\theta} \right]. \quad (19)$$

We now simplify this last expression:

$$P_i^* = C \left[1 - \frac{\eta \sum_{d=1}^{n-1} b_d}{\theta} \right] + \theta q_i + \frac{\eta}{\theta} \sum_{d=1}^{n-1} b_d P_{i-d} - \frac{\eta^2 \sum_{d=1}^{n-1} b_d \sum_{j=1}^{n-1} b_j q_{(i-d)-j}}{\theta}. \quad (20)$$

Using the fact that $\sum_{d=1}^{n-1} b_d = (1-b_0)$, we can rewrite P_i^* as:

$$P_i^* = C\left[1 - \frac{\eta(1-b_0)}{\theta}\right] + \theta q_i + \frac{\eta}{\theta}\sum_{d=1}^{n-1} b_d P_{i-d} - \frac{\eta^2 \sum_{d=1}^{n-1}\sum_{j=1}^{n-1} b_d b_j q_{(i-d)-j}}{\theta}. \tag{21}$$

Notice that the double-summation term iterates through all physicians' c_i along the circle (i.e., $i \in 0, 1, .., n-1$). Thus, we can reduce the double summation to a single summation form:

$$\sum_{d=1}^{n-1}\sum_{j=1}^{n-1} b_d b_j q_{(i-d)-j} \Rightarrow \sum_{\tilde{d}=0}^{n-1} w_{\tilde{d}} q_{i-\tilde{d}}. \tag{22}$$

We derive the coefficient $w_{\tilde{d}}$ in the following. Note that $w_{\tilde{d}}$ includes terms $b_d b_j$ at different values of j and d that need to be aggregated. The Table below shows the values of $d+j$ that correspond to each value of $\tilde{d}$. Given that $d, j \in 1, ..., n-1$, we have $d+j = \tilde{d}$ and $d+j = n+\tilde{d}$. And the lower and upper bounds of the subscript of q, $i-d-j$, are $i-(2n-2)$ and $i-2$, respectively.

$\tilde{d}$	**Feasible Values of $d+j$**	**Feasible Values of d and j**	**Comment**
0	N	$d \in \{1, ..., n-1\}$, $j = n-d$	• 0 is not a feasible value for $d+j$ because $2 \le d+j \le 2N-2$
1	$n+1$	$d \in \{2, ..., n-1\}$, $j = n+1-d$	• 1 is not a feasible value for $d+j$ because $2 \le d+j \le 2N-2$ • There is no solution for $d+j$ if $d = 1$ or $j = 1$
2	$2, n+2$	$d \in \{1, 3, ..., n-1\}$, $j = n+2-d$	• There is no solution for $d+j$ if $d = 2$ or $j = 2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$n-2$	$n-2, 2n-2$	$d \in \{1, 2, ..., n-3, n-1\}$, $d = n-2-j$	• There is no solution for $d+j$ if $d = N-2$ or $j = N-2$
$n-1$	$n-1$	$d \in \{1, 2, ..., n-3, n-2\}$, $d = n-1-j$	• $2N-1$ is not a feasible value for $d+j$ because $2 \le d+j \le 2N-2$ • There is no solution for $d+j$ if $d = N-1$ or $j = N-1$

Consequently, for $\tilde{d} = 0$, we have $d+j = n$ only so that $w_0 = \sum_{d=1}^{n-1} b_d b_{n-d} = \sum_{d=1}^{n-1} b_d^2$.
For $\tilde{d} = 1$, we have $d+j = n+1$ only so that $w_1 = \sum_{d=2}^{n-1} b_d b_{n+1-d}$.
For $\tilde{d} = n-1$, we have $d+j = n-1$ only so that $w_{n-1} = \sum_{d=1}^{n-2} b_d b_{n-1-d}$
For $\tilde{d} = \{2, ..., n-2\}$, $d+j$ can be equal to both $\tilde{d}$ and $N+\tilde{d}$, thus

$$w_{\tilde{d}} = \sum_{d=1}^{\tilde{d}-1} b_d b_{\tilde{d}-d} + \sum_{d=\tilde{d}+1}^{n-1} b_d b_{n+\tilde{d}-d} = \sum_{d=1, d\neq\tilde{d}}^{n-1} b_d b_{n+\tilde{d}-d}. \tag{23}$$

We can now rewrite the expression for the optimal physician price as:

$$P_i^* = C\left[1 - \frac{\eta(1-b_0)}{\theta}\right] + \theta q_i + \frac{\eta}{\theta}\sum_{d=1}^{n-1} b_d P_{i-d} - \frac{\eta^2 \sum_{\tilde{d}=0}^{n-1} w_{\tilde{d}} q_{i-\tilde{d}}}{\theta}. \tag{24}$$

As we can see, the sum for the quality of neighbors includes $\tilde{d} = 0$ that is the quality of physician i. We thus extract this term to rewrite the optimal price for physician i in this way:

$$P_i^* = C\left[1 - \frac{\eta(1-b_0)}{\theta}\right] + \theta q_i + \frac{\eta}{\theta}\sum_{d=1}^{n-1} b_d P_{i-d} - \frac{\eta^2}{\theta} w_0 q_i - \frac{\eta^2 \sum_{\tilde{d}=1}^{n-1} w_{\tilde{d}} q_{i-\tilde{d}}}{\theta}. \tag{25}$$

Finally, we simplify the expression for the equilibrium price as:

$$P_i^* = C + \rho \sum_{d=1}^{n-1} b_d P_{i-d}^* + \phi q_i + \lambda \sum_{\tilde{d}=1}^{n-1} w_{\tilde{d}} q_{i-\tilde{d}}. \tag{26}$$

where $C = \left[1 - \frac{\eta(1-b_0)}{\theta}\right](tl + \delta h - \overline{p} + \varepsilon)$, $\phi = \frac{\theta^2 - \eta^2 w_0}{\theta}$, $\rho = \frac{\eta}{\theta}$ and $\lambda = \frac{\eta^2}{\theta}$.

Note that for simplicity, we will rewrite equilibrium prices equation system given by (24) in a matrix format. Let's define $w_i p = \sum_{d=1}^{n-1} b_d P_{i-d}^*$ where w_i is a $1 \times n$ vector and p is a $n \times 1$ vector of price. The system of $w_i p$ for all physicians can then be write as Wp where W is a $n \times n$ matrix where row vector are given by w_i. Having these notations in mind, we can easily rewrite equilibrium prices equation system given by (24) as:

$$p = \rho W p + XB + \theta q + \lambda [W \times W] q. \tag{27}$$

In the same way we rewrite (24) into (26), we can rewrite (27) as:

$$p = \rho W p + XB + \phi q + \lambda [W \times W - diag(W \times W)] q.$$

$$p = \rho W p + XB + \phi q + \lambda \overline{q}, \tag{28}$$

with $\overline{q} = [W \times W - diag(W \times W)]q$.

Appendix B: Information on Spatial Weighting Matrices

Table B.1 shows the information of different spatial matrices used in the paper.

Ophthalmologists				
Elements	W_{exp}	W_1	W_{12}	W_{123}
Minimum weight > 0	*5.88e-39*	*5.97e-39*	*5.89e-39*	*5.89e-39*
Mean weight	*0.0005974*	*0.0005974*	*0.0005974*	*0.0005974*
Non zero weights (%)		*0.409*	*1.325*	*2.944*
Mean neighbors		*7*	*22*	*49*
Gynecologists				
Elements	W_{exp}	W_1	W_{12}	W_{123}
Minimum weight > 0	*5.88e-39*	*7.11e-39*	*6.02e-39*	*5.93e-39*
Mean weight	*0.0005371*	*0.0005371*	*0.0005371*	*0.0005371*
Non zero weights (%)		*0.390*	*1.261*	*2.833*
Mean neighbors		*7*	*23*	*53*
Pediatricians				
Elements	W_{exp}	W_1	W_{12}	W_{123}
Minimum weight > 0	*5.88e-39*	*7.56e-39*	*6.55e-39*	*5.93e-39*
Mean weight	*0.0016779*	*0.0016779*	*0.0016779*	*0.0016779*
Non zero weights (%)		*1.087*	*3.480*	*7.553*
Mean neighbors		*6*	*21*	*45*

Table B.1: Information of spatial weighting matrices under exponential function.

Appendix C: Estimation results when France is considered as a single market

	Ophthalmologists			Gynecologists			Pediatricians		
Models	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GENDER	-2.138^{***}	-1.739^{***}	-2.038^{***}	-3.144^{***}	-3.008^{***}	-2.851^{***}	-1.802^{***}	-2.095^{***}	-1.813^{***}
	(0.319)	(0.274)	(0.296)	(0.338)	(0.285)	(0.191)	(0.576)	(0.468)	(0.493)
LIBERAL	0.247	0.421^{**}	0.510	0.715^{*}	0.820^{**}	0.821^{**}	-2.648^{***}	-2.825^{***}	-2.648^{***}
	(0.407)	(0.198)	(0.374)	(0.379)	(0.390)	(0.323)	(0.503)	(0.572)	(0.571)
MEDIAN	0.263^{***}	0.272^{***}	0.259^{***}	0.471^{***}	0.403^{***}	0.454^{***}	0.251^{***}	0.247^{***}	0.199^{***}
	(0.050)	(0.045)	(0.049)	(0.059)	(0.056)	(0.054)	(0.068)	(0.064)	(0.065)
POPD	0.147^{**}	0.154^{***}	0.124^{**}	0.181^{***}	0.127^{*}	0.121^{**}	0.018	−0.010	−0.043
	(0.057)	(0.050)	(0.056)	(0.062)	(0.067)	(0.060)	(0.059)	(0.064)	(0.066)
ADISTANCE	-0.031^{**}	−0.009	−0.006	-0.051^{***}	-0.026^{**}	−0.005	0.041^{**}	0.024^{**}	0.016^{*}
	(0.013)	(0.007)	(0.008)	(0.019)	(0.012)	(0.008)	(0.019)	(0.011)	(0.009)
SHARE S2	2.276^{***}	6.004^{***}	6.848^{***}	2.071^{***}	6.614^{***}	7.730^{***}	4.466^{***}	8.212^{***}	11.385^{***}
	(0.450)	(0.442)	(1.125)	(0.698)	(1.171)	(1.238)	(1.328)	(1.416)	(2.021)
RATING	−0.001	0.094	0.006	0.144	0.305^{**}	0.283^{**}	−0.114	−0.056	−0.003
	(0.120)	(0.127)	(0.120)	(0.139)	(0.138)	(0.129)	(0.293)	(0.277)	(0.276)
C-RATING	0.037^{***}	0.044^{***}	0.034^{***}	0.057^{***}	0.061^{***}	0.058^{***}	0.024	0.027	0.020
	(0.012)	(0.011)	(0.012)	(0.012)	(0.014)	(0.013)	(0.043)	(0.041)	(0.041)
IMR	-2.293^{***}	-2.324^{***}	-2.505^{***}	-2.279^{***}	-1.283^{*}	-1.808^{***}	−1.924	−1.333	−1.131
	(0.705)	(0.462)	(0.422)	(0.673)	(0.659)	(0.700)	(1.436)	(1.100)	(1.341)
$\overline{\text{RATING}}$	-0.295^{***}	-0.316^{***}	-0.418^{***}	−0.131	−0.114	−0.030	−0.253	-0.304^{**}	-0.365^{**}
	(0.098)	(0.111)	(0.114)	(0.141)	(0.153)	(0.140)	(0.155)	(0.143)	(0.143)
$W \times$ PRICE	0.441^{***}	0.404^{***}	0.400^{***}	0.314^{***}	0.298^{***}	0.295^{***}	0.352^{***}	0.365^{***}	0.371^{***}
	(0.016)	(0.014)	(0.017)	(0.035)	(0.036)	(0.042)	(0.050)	(0.045)	(0.044)
N	1674	1674	1674	1862	1862	1862	596	596	596
$RMSE$	10.582	10.523	10.538	10.880	10.837	10.847	9.000	8.992	9.001

Note: Constant terms are omitted. Standard errors in parentheses. GMM estimation with robust het s.e. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.1: Estimation of the Spatial Durbin Models using City/District Fixed Effects.

Appendix D: Estimation results under different F.E to control location choice bias

	Ophthalmologists			Gynecologists			Pediatricians		
Models	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GENDER	-2.407^{***}	-2.412^{***}	-2.253^{***}	-2.482^{***}	-2.309^{***}	-2.517^{***}	-1.838^{**}	-1.938^{**}	-1.718^{**}
	(0.549)	(0.567)	(0.565)	(0.597)	(0.567)	(0.563)	(0.753)	(0.759)	(0.773)
LIBERAL	1.086^{*}	1.294^{**}	1.240^{*}	1.013	1.242^{*}	1.194	-2.908^{***}	-3.259^{***}	-2.932^{***}
	(0.636)	(0.645)	(0.644)	(0.731)	(0.755)	(0.752)	(0.709)	(0.709)	(0.725)
MEDIAN	0.419^{***}	0.459^{***}	0.464^{***}	0.406^{***}	0.399^{***}	0.370^{***}	0.440^{***}	0.415^{***}	0.377^{***}
	(0.091)	(0.092)	(0.089)	(0.090)	(0.089)	(0.089)	(0.097)	(0.089)	(0.091)
POPD	-0.039	-0.045	-0.048	0.015	0.009	-0.007	0.136	0.063	0.064
	(0.069)	(0.070)	(0.070)	(0.077)	(0.078)	(0.078)	(0.097)	(0.097)	(0.100)
ADISTANCE	-0.043^{***}	-0.022^{**}	-0.014	-0.040^{*}	-0.024	-0.010	0.031^{*}	0.001	0.003
	(0.015)	(0.011)	(0.009)	(0.024)	(0.018)	(0.014)	(0.016)	(0.012)	(0.011)
SHARE S2	2.092^{**}	4.872^{***}	2.949	2.139^{*}	4.595^{**}	6.733^{**}	4.234^{***}	11.151^{***}	13.563^{***}
	(0.963)	(1.768)	(2.488)	(1.258)	(1.992)	(3.009)	(1.518)	(2.886)	(3.753)
RATING	0.120	0.139	0.160	0.381	0.414^{*}	0.450^{*}	-0.001	-0.002	0.059
	(0.215)	(0.219)	(0.221)	(0.234)	(0.232)	(0.232)	(0.323)	(0.314)	(0.343)
C-RATING	0.028	0.024	0.022	0.048^{**}	0.053^{**}	0.052^{**}	0.016	0.026	0.045
	(0.020)	(0.020)	(0.020)	(0.024)	(0.023)	(0.024)	(0.049)	(0.050)	(0.047)
IMR	4.538^{**}	4.283^{**}	2.913	1.432	2.631	2.208	-0.085	0.104	0.886
	(2.103)	(2.090)	(2.053)	(2.444)	(2.562)	(2.563)	(1.537)	(1.692)	(1.724)
$\overline{\text{RATING}}$	-0.191	-0.289	-0.273	0.142	0.007	0.048	-0.410^{**}	-0.439^{***}	-0.539^{***}
	(0.229)	(0.225)	(0.226)	(0.218)	(0.209)	(0.206)	(0.178)	(0.168)	(0.158)
$W \times$PRICE	0.321^{***}	0.249^{***}	0.271^{***}	0.481^{***}	0.494^{***}	0.507^{***}	0.372^{***}	0.329^{***}	0.356^{***}
	(0.051)	(0.061)	(0.052)	(0.077)	(0.082)	(0.086)	(0.082)	(0.075)	(0.070)
N	1674	1674	1674	1862	1862	1862	596	596	596
$RMSE$	10.847	10.731	10.752	11.371	11.317	11.298	9.512	9.544	9.582

Note: Constant terms are omitted. Standard errors in parentheses. GMM estimation with robust het s.e. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.1: Estimation of the Spatial Lag Models using NUTS3 Fixed Effects.

Appendix E: Estimation results when using a different competition measure

	Ophthalmologists			Gynecologists			Pediatricians		
Models	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GENDER	-2.073^{***}	-2.249^{***}	-2.296^{***}	-3.109^{***}	-2.994^{***}	-3.154^{***}	-1.648^{***}	-1.530^{**}	-1.412^{**}
	(0.322)	(0.296)	(0.293)	(0.297)	(0.357)	(0.361)	(0.618)	(0.630)	(0.629)
LIBERAL	0.450	0.432^{*}	0.370	0.925^{**}	1.014^{***}	0.786^{*}	-2.620^{***}	-2.567^{***}	-2.545^{***}
	(0.292)	(0.261)	(0.249)	(0.363)	(0.385)	(0.407)	(0.582)	(0.583)	(0.580)
MEDIAN	0.343^{***}	0.267^{***}	0.250^{***}	0.469^{***}	0.451^{****}	0.540^{***}	0.289^{***}	0.276^{***}	0.267^{***}
	(0.050)	(0.051)	(0.050)	(0.058)	(0.058)	(0.052)	(0.071)	(0.070)	(0.070)
POPD	0.212^{***}	0.151^{***}	0.123^{**}	0.097	0.056	0.037	0.051	0.029	0.000
	(0.055)	(0.057)	(0.061)	(0.068)	(0.053)	(0.058)	(0.058)	(0.063)	(0.064)
ADISTANCE - S2	-0.025^{***}	-0.032^{***}	-0.028^{***}	-0.081^{***}	-0.041^{***}	-0.021^{***}	−0.000	−0.009	-0.010^{*}
	(0.009)	(0.006)	(0.004)	(0.011)	(0.007)	(0.005)	(0.010)	(0.007)	(0.005)
RATING	−0.064	−0.043	−0.019	0.171	0.147	0.134	−0.234	−0.124	−0.084
	(0.138)	(0.140)	(0.120)	(0.131)	(0.148)	(0.150)	(0.296)	(0.300)	(0.303)
C-RATING	0.039^{***}	0.033^{***}	0.032^{***}	0.064^{***}	0.063^{***}	0.058^{***}	0.055	0.036	0.035
	(0.012)	(0.011)	(0.011)	(0.013)	(0.014)	(0.014)	(0.042)	(0.044)	(0.044)
IMR	-3.298^{***}	-2.469^{***}	-2.263^{***}	−1.149	−1.179	-1.699^{**}	-2.754^{**}	-2.443^{*}	-2.407^{*}
	(0.714)	(0.595)	(0.474)	(0.859)	(0.909)	(0.816)	(1.366)	(1.415)	(1.416)
$\overline{\text{RATING}}$	-0.474^{***}	-0.378^{***}	-0.336^{***}	0.138	−0.015	−0.015	-0.383^{**}	-0.302^{*}	-0.279^{*}
	(0.115)	(0.115)	(0.115)	(0.136)	(0.144)	(0.146)	(0.150)	(0.156)	(0.158)
$W\times$PRICE	0.364^{***}	0.420^{***}	0.434^{***}	0.274^{***}	0.322^{***}	0.343^{***}	0.344^{***}	0.318^{***}	0.297^{***}
	(0.021)	(0.020)	(0.019)	(0.036)	(0.041)	(0.039)	(0.054)	(0.056)	(0.056)
N	1674	1674	1674	1862	1862	1862	596	596	596
$RMSE$	10.650	10.590	10.589	10.852	10.889	10.900	8.975	8.990	8.991

Note: Constant terms are omitted. Standard errors in parentheses. GMM estimation with robust het s.e. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.1: Estimation of the Spatial Lag Models using City/District Fixed Effects.

References

Ahlfeldt, G. and Pietrostefani, E. (2019). The economic effects of density: A synthesis. *Journal of Urban Economics*, 111:93–107.

Alderighi, M. and Piga, C. (2008). The circular city with heterogeneous firm. *Department of Economics Loughborough University. Loughborough, Leicestershir UK, WP*, 3.

Alderighi, M. and Piga, C. (2012). Localized competition, heterogeneous firms and vertical relations. *The Journal of Industrial Economics*, 60(1):46–74.

Alderighi, M. and Piga, C. (2014). Selection, heterogeneity, and entry in professional markets. *Journal of Economics & Management Strategy*, 23(4):925–951.

Anselin, L. (1988). *Spatial econometrics: Methods and models*, volume 4. Kluwer Academic Publishers, Dordrecht.

Arbia, G., Bera, A., Doğan, O., and Taşpınar, S. (2020). Testing impact measures in spatial autoregressive models. *International Regional Science Review*, 43(1-2):40–75.

Arneill, A. and Devlin, A. S. (2002). Perceived quality of care: The influence of the waiting room environment. *Journal of Environmental Psychology*, 22(4):345–360.

Baltagi, B., Moscone, F., and Santos, R. (2018). *Spatial Health Econometrics*, volume 294 of *Contributions to Economic Analysis*, chapter 14, pages 305 – 356. Emerald Group Publishing Limited.

Barlet, M. and Collin, C. (2009). Localisation des professionnels de santé libéraux. *Comptes Natx Santé*, 27:56.

Bellamy, V. and Samson, A.-L. (2011). Choix du secteur de conventionnement et déterminants des dépassements d'honoraires des médecins. *Les Comptes nationaux de la santé 2010*, pages 53–85.

Boots, B. and South, R. (1997). Modeling retail trade areas using higher-order, multiplicatively weighted Voronoi diagrams. *Journal of Retailing*, 73(4):519–536.

Chamberlin, E. H. (1949). *Theory of monopolistic competition: A re-orientation of the theory of value.* Oxford University Press, London.

Choné, P., Coudin, E., and Pla, A. (2019). Does the provision of physician services respond to competition? Technical report, Center for Research in Economics and Statistics.

CNAM (2011). Médecins exerçant en secteur 2: une progression continue des dépassements d'honoraires, la nécessité d'une réforme structurelle du système. *Caisse Nationale d'Assurance Maladie.*

CNAM (2014). Dépassements d'honoraires 2013 : Observatoire des pratiques tarifaires. sl: Annuaire sécu. *Caisse Nationale d'Assurance Maladie.*

CNAM (2018). Les dépassements d'honoraires et l'OPTAM: Garantir l'accès aux soins et améliorer l'efficacité du système pour mieux le préserver. *Caisse Nationale d'Assurance Maladie.*

CNAMTS (2017). Dépassements d'honoraires des médecins: une tendance à la baisse qui se confirme. Résultats de l'observatoire des pratiques tarifaires. *Caisse Nationale d'Assurance Maladie des Travailleurs Salariés.*

Combes, P., Duranton, G., and Gobillon, L. (2018). The costs of agglomeration: House and land prices in French cities. *The Review of Economic Studies*, 86(4):1556–1589.

Coudin, E., Pla, A., and Samson, A.-L. (2015). Gp responses to price regulation: evidence from a French nationwide reform. *Health Economics*, 24(9):1118–1130.

Delattre, E. and Dormont, B. (2003). Fixed fees and physician-induced demand: A panel data study on French physicians. *Health Economics*, 12(9):741–754.

Directorate General of the French Treasury (2019). Comment lutter contre les déserts médicaux? Technical Report Trésor-Eco no. 247, Ministère de l'Économie et des Finances.

DRESS (2020). Médecins en secteur 2: les dépassements d'honoraires diminuent quand la concurrence s'accroît. *Direction de la Recherche, des Études, de l'Evaluation et des Statistiques.*

Emmert, M., Meszmer, N., and Sander, U. (2016). Do health care providers use online patient ratings to improve the quality of care? results from an online-based cross-sectional study. *Journal of Medical Internet Research*, 18(9):e254.

Evans, R. G. (1974). Supplier-induced demand: some empirical evidence and implications. In *The economics of health and medical care*, pages 162–173. Springer.

Feldman, R. and Sloan, F. (1988). Competition among physicians, revisited. *Journal of Health Politics, Policy and Law*, 13(2):239–261.

Franzese, R. J. and Hays, J. C. (2007). Spatial econometric models of cross-sectional interdependence in political science panel and time-series-cross-section data. *Political Analysis*, 15(2):140–164.

Fuchs, V. (1978). The supply of surgeons and the demand for operations. Technical report, National Bureau of Economic Research.

Gaynor, M. and Town, R. (2012). Competition in health care markets. In *Handbook of Health Economics*, volume 2, pages 499–637. Elsevier.

Grabner-Kräuter, S. and Waiguny, M. (2015). Insights into the impact of online physician reviews on patients' decision making: randomized experiment. *Journal of Medical Internet Research*, 17(4):e93.

Gravelle, H., Liu, D., Propper, C., and Santos, R. (2019). Spatial competition and quality: Evidence from the English family doctor market. *Journal of Health Economics*, 68:102249.

Gravelle, H., Santos, R., and Siciliani, L. (2014). Does a hospital's quality depend on the quality of other hospitals? a spatial econometrics approach. *Regional Science and Urban Economics*, 49:203–216.

Gravelle, H., Scott, A., Sivey, P., and Yong, J. (2016). Competition, prices and quality in the market for physician consultations. *The Journal of Industrial Economics*, 64(1):135–169.

Greaves, F. and Millett, C. (2012). Consistently increasing numbers of online ratings of healthcare in England. *Journal of Medical Internet Research*, 14(3):e94.

Haddad, S., Potvin, L., Roberge, D., Pineault, R., and Remondin, M. (2000). Patient perception of quality following a visit to a doctor in a primary care unit. *Family Practice*, 17(1):21–29.

Hensgen, F., Paris, V., Pierrard, B., and Vergeau, A. (2000). Charges professionnelles des médecins libéraux. étude préparatoire à la refonte de la tarificationdes actes médicaux. *CREDES. Centre de Recherche d'Étude et de Documentation en Économie de la Santé*, 499 (biblio no. 1321).

Hondroyiannis, G., Kelejian, H., and Tavlas, G. (2009). Spatial aspects of contagion among emerging economies. *Spatial Economic Analysis*, 4(2):191–211.

Johar, M. (2012). Do doctors charge high income patients more? *Economics Letters*, 117(3):596–599.

Johnson, E. (2014). Physician-induced demand. In Culyer, A. J., editor, *Encyclopedia of Health Economics*, pages 77 – 82. Elsevier, San Diego.

Kelejian, H. and Prucha, I. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The Journal of Real Estate Finance and Economics*, 17(1):99–121.

Kelejian, H. and Prucha, I. (1999). A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review*, 40(2):509–533.

Kelejian, H. and Prucha, I. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, 157(1):53–67.

Kim, C., Phipps, T., and Anselin, L. (2003). Measuring the benefits of air quality improvement: a spatial hedonic approach. *Journal of Environmental Economics and Management*, 45(1):24–39.

Kumar, A., de Lagasnerie, G., Maiorano, F., and Forti, A. (2014). Pricing and competition in specialist medical services. *OECD Health Working Papers*.

Le Gallo, J., Ertur, C., and Baumont, C. (2003). A spatial econometric analysis of convergence across European regions, 1980-1995. In Fingleton, B., editor, *European Regional Growth*, chapter 3, pages 99–129. Springer.

LeSage, J. and Pace, R. (2009). *Introduction to spatial econometrics*. Statistics: A Series of Textbooks and Monographs. Chapman and Hall, CRC press.

Levine, R., Shore, K., Lubalin, J., Garfinkel, S., Hurtado, M., and Carman, K. (2012). Comparing physician and patient perceptions of quality in ambulatory care. *International Journal for Quality in Health Care*, 24(4):348–356.

Lin, M. and Wu, R. (2015). Production cost heterogeneity in the circular city model. *Operations Research Letters*, 43(4):401–404.

Longo, F., Siciliani, L., Gravelle, H., and Santos, R. (2017). Do hospitals respond to rivals' quality and efficiency? a spatial panel econometric analysis. *Health economics*, 26:38–62.

McGrath, R., Priestley, J. L., Zhou, Y., and Culligan, P. (2018). The validity of online patient ratings of physicians: analysis of physician peer reviews and patient ratings. *Interactive Journal of Medical Research*, 7(1):e8.

McGuire, T. G. (2000). Physician agency. In *Handbook of Health Economics*, volume 1, chapter 9, pages 461–536. Elsevier.

McGuire, T. G. and Pauly, M. V. (1991). Physician response to fee changes with multiple payers. *Journal of Health Economics*, 10(4):385–410.

Mobley, L., Frech III, H., and Anselin, L. (2009). Spatial interaction, spatial multipliers and hospital competition. *International Journal of the Economics of Business*, 16(1):1–17.

Newhouse, J. P. (1970). A model of physician pricing. *Southern Economic Journal*, pages 174–183.

OECD (2016). *Geographic imbalances in the distribution of doctors and health care services in OECD countries*, chapter Chapter 5, pages 129–162. OECD.

O'sullivan, D. and Unwin, D. (2010). *Geographic information analysis*. John Wiley & Sons, second edition.

Pál, V., Lados, G., Ilcsikné Makra, Z., Boros, L., Uzzoli, A., and Fabula, S. (2021). Concentration and inequality in the geographic distribution of physicians in the European Union, 2006–2018. *Regional Statistics*, 11(3):3–28.

Pauly, M. V. and Satterthwaite, M. A. (1981). The pricing of primary care physicians services: a test of the role of consumer information. *The Bell Journal of Economics*, pages 488–506.

Reinhardt, U. (1985). The theory of physician-induced demand reflections after a decade. *Journal of Health Economics*, 4(2):187–193.

Rice, T. (1983). The impact of changing Medicare reimbursement rates on physician-induced demand. *Medical Care*, pages 803–815.

Richardson, J. R., Peacock, S. J., and Mortimer, D. (2006). Does an increase in the doctor supply reduce medical fees? an econometric analysis of medical fees across Australia. *Applied Economics*, 38(3):253–266.

Rizzo, J. and Blumenthal, D. (1996). Is the target income hypothesis an economic heresy? *Medical Care Research and Review*, 53(3):243–266.

Rochaix, L. and Jacobzone, S. (1997). L'hypothèse de demande induite: un bilan économique. *Économie & prévision*, 129(3):25–36.

Rothschild, R. (1982). Competitive behaviour in chain-linked markets. *The Journal of Industrial Economics*, pages 57–67.

Rüttenauer, T. (2019). Spatial regression models: a systematic comparison of different model specifications using Monte Carlo experiments. *Sociological Methods & Research*, page 0049124119882467.

Siciliani, L., Moran, V., and Borowitz, M. (2014). Measuring and comparing health care waiting times in OECD countries. *Health Policy*, 118(3):292–303.

Sivey, P. and Chen, Y. (2019). Competition and quality in healthcare. *Oxford Research Encyclopedia of Economics and Finance*.

Stano, M. (1985). An analysis of the evidence on competition in the physician services markets. *Journal of Health Economics*, 4(3):197–211.

Stano, M. (1987). A further analysis of the physician inducement controversy. *Journal of Health Economics*, 6(3):227–238.

Steinwald, B. and Sloan, F. A. (1974). Determinants of physicians' fees. *The Journal of Business*, 47(4):493–511.

Tirole, J. (1988). *The theory of industrial organization.* MIT press.

Wedig, G., Mitchell, J., and Cromwell, J. (1989). Can price controls induce optimal physician behavior? *Journal of Health Politics, Policy and Law*, 14(3):601–620.

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