COMPETITION, CONFORMISM AND THE LOW ADOPTION OF A GENEROUS PRICING SCHEME OFFERED TO PHYSICIANS

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Competition, conformism and the low adoption of a generous pricing scheme offered to physicians

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Abstract

This paper proposes a structural econometric approach to examine how individual decisions are influenced by various sources of interaction, modeled through a multiplex network. Specifically, we develop a binary choice model under incomplete information that captures two distinct micro-founded interaction mechanisms: spatial competition and conformity to social norms. We apply our game theoretical framework to analyze the choices made by private physicians regarding the adoption of a new pricing scheme in France, designed to enhance patient access to care while being economically beneficial for most physicians. Our analysis utilizes a unique geolocalized dataset that covers the entire population of physicians across three medical specialties. We find compelling evidence of a significant preference for conformity, while competitive interactions in physician decision appear minimal. These findings largely explain the low adoption rates of the new pricing scheme, as simulations and counterfactual analyses suggest that a substantially higher uptake rate would occur if physicians operated in isolation or were indifferent to conformity. Lastly, we discuss the implications of neglecting relevant sources of interaction in a structural model, which can lead to ineffective policy design.

JEL Classification: D04, I11, I18

Keywords: binary choice, competition, social interactions, pricing scheme, physicians

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1 Introduction

Healthcare costs are the primary reason for patients to forgo care (Daabek et al. 2022). This affordability issue is further exacerbated by the ongoing and sustained increase in healthcare spending, a challenge experienced by most countries, regardless of the organization and financing of their healthcare systems. Consequently, reducing the growth rate of healthcare expenditures has emerged as a priority for governments, particularly in nations where healthcare spending constitutes a substantial portion of GDP, such as the United States, France, Germany, and Japan. However, as noted in Alexander (2020), there is no consensus on effective policies to mitigate costs, necessitating that governments explore and implement a variety of strategies.

Some recent economic studies have explored how healthcare providers respond to financial incentives (Alexander 2020, Alexander & Schnell 2024) and examined the efficiency of voluntary versus mandatory regulations (Einav et al. 2022). Although these articles provide detailed microeconomic analyses, often at the physician level, the majority focus on specific pilot programs implemented in a limited number of hospitals or particular physician activities (e.g., surgeries) within those hospitals. These analyses typically utilize randomized policy implementations to estimate causal effects. However, the generalizability of such small-scale interventions is often limited due to the high spatial and specialty heterogeneity within the medical sector. More importantly, to our knowledge, the existing literature has largely overlooked the possibility that physicians' responses to financial incentives may be influenced by their peers' behaviors. This is surprising given the significant interdependencies among practitioners, whether through Accountable Care Organizations in the United States or professional unions in France. Consequently, little is known about how peer effects shape physician behavior and, in turn, how these dynamics affect the efficiency of regulations.

In this paper, we propose a structural econometric approach including peer effects to evaluate the adoption of a new pricing scheme offered on a voluntary basis to all French physicians, using a unique database covering the population of private physicians in three specialties (ophthalmology, gynecology, and pediatrics). This pricing scheme, referred to as the "Contrat d'accès aux Soins" (CAS hereafter), was introduced primarily to improve patients' access to affordable healthcare by addressing the persistent increase in extra fees charged by private physicians, which surged from 1.6 billion euros in 2005 to 3.5 billion euros in 2021. Like many countries, France faces significant challenges regarding both the financial and geographical accessibility of healthcare, making this a longstanding and pressing political issue.

Under the CAS pricing scheme, participating physicians are required to freeze or reduce their fees if they exceed, on average, 200% of the regulated fees (hereafter referred to as the CAS price ceiling). In return, CAS adopters receive tax advantages and are allowed to increase fees for specific medical acts provided at regulated fees. Moreover, CAS enhances reimbursement rates for their patients. A critical aspect of the CAS design is its voluntary participation framework. As noted in Einav et al. (2022), voluntary programs are popular among physicians because they align with their preferences for autonomy of medical practice, including freedom of choice and aversion to government control. The effectiveness of such programs depends on the generation of favorable selection on *slopes* rather than on *levels*. In our context, the policy design naturally leads to selection on levels, as physicians whose fees are below the CAS price ceiling can benefit from the contract without altering their pricing behavior. However, achieving selection on slopes requires a substantial proportion of physicians with fees above the CAS price ceiling to opt into the program. This outcome may arise if, for instance, the competitive pressure exerted by CAS adopters (through patient poaching) is sufficiently strong or if the local norm is to adopt the CAS (assuming physicians have a preference for conformity).

CAS has encountered limited success, with only a small proportion of physicians opting for the new pricing scheme. Analysis of CAS conditions and physician pricing behavior reveals two key empirical patterns: (i) a significant number of physicians who could financially benefited from the CAS chose not to adopt it, and (ii) there are pronounced spatial disparities in the CAS adoption rates[1]. These observations indicate low and spatially heterogeneous selection on levels, suggesting that physicians' decisions are only partially driven by individual financial incentives. As previously noted, peer interactions are likely to play a significant role in influencing these choices.

Private physicians' decisions to adopt or not the new pricing scheme provide a unique and well-suited case for studying two major types of interactions among peers on a multiplex network, thereby extending the literature on peer effects. On the one hand, physicians constitute a distinct professional group within society, characterized by a strong sense of belonging and shared interests. These common interests are institutionally defended by various organizations[2]. Additionally, the practice and organization of care involve frequent interactions with peers, which further reinforce social bonds[3]. Thus, social interactions constitute the first layer of the multiplex network. On the other hand, a private physician operates as a small business owner and may engage in strategic interactions with nearby competitors, that is, in spatial competition. Given that patients value proximity, price, and quality of care, horizontal and vertical differentiation strategies may emerge in areas well-endowed with medical services. Consequently, competitive interactions constitute the second layer of the multiplex network.

Given the multiplex nature of the physicians' network, the net impact of peer interactions on physicians' decisions depends on the relative influence of competitive versus social interactions. Identifying the respective contributions of these interactions is challenging, and, to the best of our knowledge, has not been addressed in the literature. The correlation between individual and peer choices is moderate for various specifications of the layers of the multiplex network[4], and identifying the source of this correlation is infeasible without a structural model, originating from microeconomic theory and accounting for the multiplex game that physicians play.

In this context, the objective of this paper is two-fold. First, we aim to understand the role of two distinct sources of peer interactions in physician decisions that have been overlooked in the current literature. The development of a structural econometric approach enables us to identify these two types of interactions, which are modeled as two layers of a multiplex network. Second, we seek to quantify the extent to which these

[1]These patterns are illustrated in Figures A.1-A.3 in Appendix A, which map the non-adoption rates of physicians whose income would have increased under the CAS, assuming a constant level of activity. The data cover all liberal physicians in three medical specialties (Pediatrics, Ophthalmology, and Gynecology) for 2016. The criteria for identifying physicians who are likely to experience income increases under the CAS are detailed in Section 2.

[2]Notably, the National Council of the Physicians Order and numerous physicians' unions, which directly negotiate with the National Health Insurance (NHI) to establish the medical convention governing the rules and pricing of medical practice in France.

[3]Throughout this paper, social interactions refer to all interactions that are not induced by spatial competition.

[4]Tables A.1-A.3 in Appendix A presents correlations between individual choices and the average choices of peers, based on different specifications of the layers of the multiplex network.

competitive and social interactions account for the weak uptake of the new pricing scheme discussed above, and consequently, the low efficacy of this (costly) policy in addressing affordability issues within the French healthcare system. To achieve these objectives, this article contributes to the existing literature in several ways.

From a theoretical perspective, we introduce a binary choice model with interactions on a multiplex network, which extends the literature on the structural estimation of binary games under incomplete information (Brock & Durlauf 2001, Bajari, Hong, Krainer & Nekipelov 2010, Lee et al. 2014). To the best of our knowledge, previous studies have only considered single-layered networks [5]. Our model provides a unified framework that simultaneously accounts for two sources of interdependency among players: competitive and social interactions. This approach contrasts with existing literature on the structural estimation of games with binary action spaces, which typically focuses either on competitive interactions (Ciliberto & Tamer 2009, Pinkse et al. 2002, Bajari, Hong & Ryan 2010) or social interactions (Brock & Durlauf 2001, Lee et al. 2014). By determining the conditions for the uniqueness of equilibrium, we derive a closed-form equilibrium solution that allows us to assess the relative strength of these two sources of strategic interactions.

From a health economics perspective, our work contributes to the growing literature on the impact and optimal design of financial incentives for healthcare providers (e.g. Alexander (2020), Einav et al. (2022)) by analyzing the introduction of a new pricing scheme offered on a voluntary basis to all free-billing physicians in France. Unlike in the United States, where pilot programs are commonly used to test and design policies (Alexander 2020), most policies aimed at controlling healthcare costs in France are implemented nationwide following extensive negotiations among the government, the National Health Insurance (NHI), and physicians' unions. This contrast highlights a distinctive culture of experimentation between the two countries and underscores the significant influence of physicians' unions in France. Consequently, our study provides a novel analysis of a national policy within a markedly different context compared to the U.S. We also contribute to the literature on physicians' services markets (e.g. Gaynor & Town (2011), Brekke et al. (2010), Gravelle et al. (2016),Montmartin & Herrera-Gómez (2023)) by explicitly incorporating the influence of peers through potential spatial competition and conformity preferences, factors that are largely overlooked in the existing literature. We carefully estimate our incomplete information game theory model using the Nested Pseudo-Likelihood (NPL) estimator proposed by Aguirregabiria & Mira (2007), applying it to a unique geolocalized dataset that encompasses the entire population of private practitioners across three specialties. We place a strong emphasis on the robustness of our results before conducting counterfactual analyses.

Our empirical results lead to two main conclusions. First, we emphasize the importance of employing a structural approach to obtain unbiased estimates, thereby avoiding misinterpretations of coefficients and ineffective policy recommendations. Second, we find clear evidence that physicians' taste for conformity plays a significant role in the adoption of the new pricing scheme, whereas spatial competition does not appear to have a substantial effect. Depending on the specialty, the marginal effect of social interactions ranges from

[5] However, Zenou & Zhou (2024) propose an analysis of a game on a multiplex network with continuous action space, in which players make different decisions in each layer of the network. Chandrasekhar et al. (2024) study diffusion over a multiplex network, in which a given behavior or innovation can be spread over several layers, while Billand et al. (2023) develop a theory a network formation on multiplex networks.

0.28 to 0.45. In other words, a 10 percentage point (pp) increase in the adoption of the new pricing scheme within a physician's social group increases her probability of opting for the CAS by between 2.8 and 4.5 pp. Moreover, our counterfactual analyses highlight that the unexpectedly low adoption rate of the new pricing scheme is primarily attributable to conformity dynamics. Indeed, when the social norm among each physician's peers is to refrain from adopting the new pricing scheme, the taste for conformity discourages most physicians from embracing it, as they would deviate significantly from the norm and face considerable penalties. If all physicians were isolated on the multiplex network[6], we estimate that CAS take-up would have been between 10 and 20 pp higher, depending on the specialty.

These findings provide valuable insights for designing effective policies aimed at curbing the rise in physician fees. First, policy design should be based on realistic assumptions regarding care providers' behaviors and market characteristics. It is important not to assume that classical economic mechanisms, such as responses to financial incentives or competition, are universally applicable. For instance, most studies based on US data reveal a significant responsiveness of healthcare providers to financial incentives (Ho & Pakes 2014, Alexander 2020, Einav et al. 2022, Alexander & Schnell 2024), primarily due to an institutional framework that facilitates patient sorting, enabling providers to maximize the benefits of such incentives. Conversely, in a country like France, where sorting is not permitted (in principle), the sensitivity of care providers to financial incentives is, in practice, weaker. Importantly, acknowledging the various forms of interactions among care providers is crucial. Our findings underscore a strong preference for conformity, which, in the absence of spatial competition, diminishes the financial advantages from the pricing scheme. This results in a low adoption rate even from a selection on levels perspective. In this context, our results align with those of Einav et al. (2022), as the CAS reform was implemented on a voluntary basis, leading to selection on levels (which incurs a social cost) but virtually no selection on slopes. This raises a critical question about the effectiveness of voluntary versus mandatory policy designs in achieving desirable goals and generating welfare-enhancing outcomes.

The remainder of the paper is organized as follows. Section 2 provides an overview of the French primary care system and elaborates on the CAS pricing scheme. Section 3 develops a game on a multiplex network with a binary action space, under incomplete information, and incorporating two types of interactions. Section 4 outlines our estimation strategy along with the necessary conditions for the identification of the model's parameters. Section 5 presents our data, while Section 6 discusses our empirical results, proposes simulations and counterfactual analyses, and explores the implications of our findings for policy design. Conclusions are presented in Section 7.

[6]Or if the share of peers that adopt the CAS is exactly 50% for all physicians, in which case adopting or not the new pricing scheme results in the same distance from the norm and thus the same penalty. Physicians would then be indifferent, in the social dimension, between adopting or not adopting the pricing scheme.

2 Institutional context and the new pricing scheme contract

2.1 The French primary care system

France offers a compelling context for analyzing policies designed to reduce healthcare costs. In 2022, healthcare expenditures represented 12.1% of GDP (OECD 2023), placing France third among OECD nations. France has a slightly lower out-of-pocket (OOP) payment level than the US, with patients personally covering about 9% (10-11% in the US) of total health spending (Or et al. 2023). However, this overall figure conceals important disparities in OOP payments between ambulatory and hospital care, a distinction closely linked to a unique feature of the French healthcare system. France is among a small group of OECD countries[7] that allow some physicians to set their fees freely. As a result, a significant portion of total patients' direct OOP expenses arise from extra fees charged by free-billing physicians, which are not reimbursed by the National Health Insurance system. Using individual-level data on French patients, Perronnin (2016) found that in 2010, OOP payments represented 33% of total ambulatory care expenditures, compared to only 9% for hospital care.

French private physicians, representing approximately 60% of all physicians[8], operate on a fee-for-service basis. Nationally regulated fees for medical services, specific to each specialty, are negotiated at the national level between physicians' unions and the National Health Insurance (NHI) system. Until 2013, physicians were classified into three categories based on their pricing scheme contracts.

- Sector 1: Physicians in this category adhere to the regulated fee for all medical acts.
- Sector 2: These free-billing physicians are allowed to charge fees they want but are theoretically required to exercise "tact and moderation" and cannot balance-bill low-income patients.
- Sector 3: Representing less than 0.5% of private physicians, these physicians have no agreement with the NHI and can charge patients any price they want. Unlike the other two sectors, their patients are not reimburse from the NHI in this category and pay nearly 100% of the fees out of pocket.

The distribution of physicians between Sector 1 and Sector 2 varies significantly by specialty. In 2016, approximately 95% of general practitioners (GPs) practiced in Sector 1, whereas only 18% of surgeons, 38% of gynecologists, and 40% of ophthalmologists operated within this pricing scheme. The decision between sector 1 and sector 2 occurs at the beginning of a physician's career, with eligibility for sector 2 contingent upon additional training and qualifications. Specifically, physicians must undertake advanced public hospital training and secure positions at university hospitals, particularly as chief residents in public hospitals ("Chef de clinique" in French).

Every citizen is covered by the National Health Insurance (NHI), and all individuals are free to subscribe to private health insurance. Approximately 89% of the population has private health insurance. The NHI covers 70% of the regulated fee but does not cover any additional fees charged by physicians. Patients must pay these additional fees out-of-pocket; however, they may receive partial or full reimbursement from their

[7] Namely Australia, Austria, Belgium, France, and New Zealand (Kumar et al. 2014).
[8] The remaining doctors are primarily public servants working in public hospitals.

private insurance, depending on their coverage. Following the implementation of the CAS at the end of 2013, the government forced private insurance companies to offer a specific insurance called "contrat responsable" (responsible contract), which can be seen as the basic private insurance plan. In this type of contract, the 30% of the regulated fee that is not reimbursed by NHI is covered, as well as the additional fees for physicians who opted for CAS. Thus, additional fees from free-billing physicians are not reimbursed to patients under this contract. Finally, much more expensive private health insurances often reimburse the additional fees of sector 2 physicians up to 100% of regulated fees which corresponds to the CAS price ceiling. Consequently, most French patients have to pay part of the additional fees charged by free-billing physicians.

Patients are free to choose their physician, but in order to benefit from the 70% reimbursement from the NHI, they must designate a specific doctor, usually a general practitioner (GP) - to act as a gatekeeper who refers them to specialists when necessary. Specialists generally do not accept patients if they are not referred to by a GP. However, for certain specialists, such as gynecologists, pediatricians, ophthalmologists, psychiatrists, and dentists, patients can consult directly without a referral and still be reimbursed at 70% by the NHI. Consequently, patients' freedom of choice is limited to these specialties, guiding our empirical focus on gynecologists, pediatricians, and ophthalmologists.

For comparative purposes, Table 1 offers a concise overview of the key differences between the French and US[9] systems for private physicians regarding patient access and physician practice.

Patients' Access to Physicians

	France	**USA**
Choice of Physicians	Free	Limited by insurance networks
Global Out-of-Pocket (OOP) Costs	9% (2021)	10% (2020)
Insurance Coverage	Public insurance (70% of regulated fee) + optional private insurance	Private insurance

Physicians' Payments and Practice

	France	**USA**
Payment System	Fee-for-service (FFS) only	FFS and capitation
Level of Fees	Set by NHI (Sector 1) or fully free (Sectors 2 & 3)	Negotiated (private insurance), administratively set (public insurance), or fully free (without insurance)
Location Constraints	None	None in theory, but constrained by insurance networks and state licensing policy
Sorting of patients	Not allowed (in principle)	Allowed (based on insurance or ability to pay)

Table 1: Comparison of US and French Systems for Physicians' Services

[9] We focus on the US system here as the analyses closest to ours are based on the US context.

2.2 The new pricing scheme contract (CAS)

The steady rise in additional fees imposed by free-billing physicians has emerged as a critical political issue in France. This trend poses a threat to the stability of the social security system, especially in light of an aging population, and imposes greater financial burdens on individuals. In response, the government and the National Health Insurance (NHI) have engaged in negotiations with physician unions to establish an intermediate sector between Sectors 1 and 2, formalized as the CAS.

Since 2013, free-billing physicians have been given the option to enroll in this contract. Participating physicians agree to cap their fees at a maximum of 200% of regulated fees (referred to as the 100%-ceiling price) and to maintain or increase the proportion of medical acts performed at regulated fees. In exchange, these physicians are entitled to various benefits.

First, the regulated fee for all medical acts performed by CAS physicians is aligned with the Sector 1 fee. For instance, in 2013, the regulated fee for a consultation with most specialists was €28, which exceeded the maximum regulated fee for free-billing physicians (€23 or €25, depending on whether patients were referred by a general practitioner). Although patients of CAS physicians could be charged fees well above the regulated rate, they benefit from higher reimbursements from both NHI and private health insurance, thereby reducing their financial burden to a level very close to, if not the same as, that for patients of Sector 1 physicians.

Second, the NHI reimburses the social security contributions of physicians for all acts performed at the regulated fee, thereby directly increasing their income. The only official data available regarding the average social security benefit for physicians was provided by the NHI (2015) for the year ending in 2013. On average, the NHI reimbursed €6,950 in social security contributions per specialist physician who signed the CAS. However, this figure conceals significant disparities among specialties. According to the report, the average reimbursement ranged from €3,000 to €4,000 for gynecologists and pediatricians, while it ranged from €11,000 to €13,000 for cardiologists and radiologists. These differences are closely related to the variations in physicians' income levels. For example, in 2014, the average income of a radiologist was €216,000, compared to €106,000 for gynecologists and €84,000 for pediatricians (Cour des Comptes, 2017). Using these figures, we estimate that the social contribution reimbursed by the NHI represented, on average, a net gain of nearly 5% of the total revenue for specialist physicians[10].

The CAS is established for a three-year term but may be terminated annually on the contract's anniversary date by the physician. In such a case, the physician would revert to the sector 2 pricing scheme without incurring any associated costs.

The CAS pricing scheme was implemented on November 30, 2013, one year after negotiations between the NHI and the physicians' unions. According to NHI (Assurance Maladie 2015), 4,786 free-billing specialist physicians opted into the contract at the end of 2013, and this number increased to 5,129 at the end of 2014. The NHI report also highlights a degree of turnover, as some physicians discontinued the contract after the first year while others joined during its initial year.

[10]The average revenue of specialist physicians was €142,000 in 2014, with an average social security reimbursement of €6,950.

This information is critical for understanding the assumptions regarding the information available to physicians about their peers' decisions. Specifically, the decisions to adopt the CAS were only partially simultaneous, as only the initial contractors in 2013 were required to make their decisions at the same time each year. For these physicians, the decision to adopt the CAS was made under conditions of incomplete information. However, our analysis utilized data collected in 2016 (the last year of the CAS's existence), which also included non-initial contractors. One might argue that physicians who signed the CAS contract after the initial launch made their decisions sequentially relative to the initial contractors, thereby possessing complete information about some of their competitors and peers. Nevertheless, gathering information about other physicians' decisions is costly, as it necessitates collecting details on the pricing schemes of each potential peer or competitor via the NHI's website. Furthermore, the dynamic nature of the decision-making process introduces additional uncertainty. Even if an individual initially gathers accurate data on peers' pricing schemes when making their decision, the choices of some peers may change during the administrative transition to the CAS. Consequently, it appears more appropriate to model the overall decision to adopt the CAS as a game characterized by incomplete information regarding the actions of other players. In this framework, physicians do not perfectly observe the decisions of their peers concerning the adoption of the CAS and form rational expectations based on available information, which subsequently influences their own decisions to adopt the new pricing scheme through dynamics of competition and conformity.

3 Structural model of competitive and social interactions on a multiplex network

We propose a binary choice model with incomplete information, inspired by social interaction models (Brock & Durlauf 2001, Bajari, Hong, Krainer & Nekipelov 2010, Lee et al. 2014), incorporating interactions across two layers of a multiplex network. Our model is microfounded using a game-theoretic approach on a network, recognizing that players—specifically physicians—may compete with certain peers on the first layer while conforming to norms among (potentially) distinct peers on the second layer.

We consider a set of n free-billing (FB) physicians, also referred to as players, denoted $\mathcal{N}$, with each physician indexed by i and $i = 1, 2, ..., n$. Each player i selects a binary action $y_i \in \mathcal{Y}_i$, where $\mathcal{Y}_i \equiv \{0, 1\}$ by convention. In our context, the binary action is to adopt the CAS ($y_i = 1$) or not ($y_i = 0$), which explains why the players are only FB physicians.

FB physicians interact with other physicians, including those in the FB sector and the regulated fee (RF) sector. Let $\mathcal{M}$ be the set of RF physicians and W a multiplex network of interactions among all $n + m$ physicians. We consider two layers of interactions: a competitive layer W^C and a social layer W^G. The former layer is defined based on spatial distance, while the latter involves colleagues with whom a physician interacts within medical or administrative institutions and professional unions (see Section 5.2). For each layer of the multiplex network W, we define two subnetworks W^F and W^R that comprise only the nodes and edges corresponding to FB and RF physicians, respectively. More formally, let $W^F = \{W_{ij} : i \in \mathcal{N}, j \in \mathcal{N}\}$ be a $n \times n$ matrix and $W^R = \{W_{ij} : i \in \mathcal{M}, j \in \mathcal{M}\}$ be a $m \times m$ matrix. By extension, W^{CF} and W^{GF} represent the competitive and social layers of the FB subnetwork of physicians, respectively. Additionally, we define a subnetwork for the competitive layer that contains the interactions between FB and RF physicians, $W^{CFR} = \{W_{ij}^{CF} : i \in \mathcal{N}, j \in \mathcal{M}\}$, as a $n \times m$ matrix. The subnetworks W^{CF} and W^{CFR} are crucial in our model, as FB physicians can engage in competitive interactions with both FB and RF physicians, while W^{GF} is used to define the local norm among FB physicians regarding the adoption of the CAS[11].

For a given matrix X, we define the i^th row as $X_i = (x_{i1}, ..., x_{in})$. In each layer k of the multiplex network, the weights w_{ij}^k represent the strength of the link between physician i and physician j. By convention, we set $w_{ii}^k = 0$ to exclude self-influence. Following the literature on spatial competition models, we assume that the weights of w_{ij}^{CF} are a function of the geographical distance between i and j and thus are continuous. Following the literature on peer effects, the weights w_{ij}^{GF} are binary, with $w_{ij}^{GF} = 1$ if i and j are connected, and 0 otherwise. Note that although the same nodes are included in both the competitive and social layers of W, the links in W^{CF} and W^{GF} are generally not linearly dependent. We thus allow situations where $w_{ij}^{CF} > 0$ and $w_{ij}^{GF} = 0$ and vice-versa, as well as positive or negative correlation between w_{ij}^{CF} and w_{ij}^{GF}.

We posit that physicians face uncertainty regarding the actions of other players due to their inability to observe the types of these players ε. Consequently, they formulate rational expectations based on the information available to them. The publicly available information includes the characteristics of physicians and the structure of the multiplex network. Thus, physicians select their strategies by evaluating expected payoffs $U^e(y_i)_{y_i \in Y_i}$. Following Brock & Durlauf (2001), we assume that U^e is an additive function, composed of the following three elements: $\Pi(\cdot)$, which represents the deterministic utility derived from gross revenue (hereafter profit), $S(\cdot)$, is the deterministic social utility, and $\varepsilon \equiv \varepsilon(y)_{y \in Y}$, which are random private utility shocks (or, more generally, players' types).

Assumption 1 *Individual random preference shocks $\varepsilon_i(y_i)_{y_i \in Y_i}$ are identically and independently distributed (i.i.d.) within and between players. Player i observes $\varepsilon_i(y_i)_{y_i \in Y_i}$, her type, but does not observe $\varepsilon_j(y_j)_{y_j \in Y_j} \forall j \neq i$.*

More specifically we set:

$$U^e(y_i) = \Pi(y_i, V_i(y_i), Z_i, W_i^{CF}, W_i^{CFR}, p) + S(y_i, W_i^{GF}, p) + \varepsilon_i(y_i)$$

$V_i(y_i)$ represents the characteristics of physician i that are endogenously influenced by y_i, whereas Z_i are exogenous characteristics of the physicians or their market. $p = (p_1, ..., p_n)$ is a $n \times 1$ vector where $p_j = \mathbb{E}[\Pr(y_j = 1|\mathbb{I})]$ is the expected probability that the physician j chooses 1 given the public information set $\mathbb{I} = \{V, Z, W^{CF}, W^{CFR}, W^{GF}\}$:

[11]We do not consider regulated-fee physicians in the social layer as they cannot choose the CAS.

Assumption 2 *Players form rational expectations regarding the actions of others, based on the information set* $\mathbb{I}$. *Let player i's rational expectation concerning player j's action be denoted as* $p_j^i = \mathbb{E}[\Pr(y_j = 1|\mathbb{I})] \in [0, 1]$.

Note that all physicians form the same expectations regarding physician j's choice, i.e. $p_j^i = p_j^k \equiv p_j, \forall k \neq i \neq j$ as the information set contains only public information. In contrast to Brock & Durlauf (2001), the expectations are heterogeneous in the sense that each player has an idiosyncratic network and specific characteristics that shape the expectations formed by others about her actions, such that $p_j = p_k \iff (V_j, Z_j, W_j^{CF}, W_j^{CFR}, W_j^{GF}) = (V_k, Z_k, W_k^{CF}, W_k^{CFR}, W_k^{GF})$. Although i is uncertain about j's choice, she perfectly observes $V_i(y_i)$, such that $V = [V(0) \;\; V(1)]$.

This framework departs from classical games on a network with a binary action space studied by Brock & Durlauf (2001), Bajari, Hong, Krainer & Nekipelov (2010), and Lee et al. (2014) in several ways. First, we employ a multiplex network to account for two distinct types of interactions among players: competition and conformity, recognizing that physicians' competitors and social peers are typically separate entities. Second, we differentiate between two types of observables that influence profit (and payoffs more broadly). The first type, denoted by V_i, is endogenously determined by y_i, whereas the second type, Z_i, is strictly exogenous, as typically assumed in the literature.

In the following section, we outline the functional forms of $\Pi(\cdot)$ and $S(\cdot)$ implemented in our study. However, our framework accommodates a wide range of functional forms, provided that the layers of the multiplex network are not perfectly correlated.[12]

3.1 The deterministic profit

We consider a framework where physicians are heterogeneous and provide differentiated horizontal (location) and vertical (quality) services to patients. They operate in monopolistic competition[13], modeled through local spatial interactions akin to the circular city model with heterogeneity as in Alderighi & Piga (2012), Lin & Wu (2015), Montmartin & Herrera-Gómez (2023). For simplicity, we assume that physicians engage solely in the consultation activity. Π represents the valuation of profit[14]. Following the classical assumption in discrete choice models, we assert that this can be described by a linear function of two elements: the gross average revenue per consultation, denoted R, and the level of demand D (number of consultations). Without loss of generality[15], we set:

$$\Pi(y_i, V_i(y_i), Z_i, W_i^{CF}, W_i^{CFR}, p) = \alpha R(V_i(y_i)) + (1-\alpha) D(Z_i, y_i, W_i^{CF}, W_i^{CFR}, p) \tag{1}$$

[12]See Lambotte (2024) for an example where $\Pi(\cdot)$ is based on the adjacency matrix and captures strategic complementarities rather than competitive interactions.

[13]Section 6 of Gaynor & Town (2011) provides a review of the literature, which shows that predictions from monopolistic competition fit physicians' pricing behaviors, whereas monopoly and perfect competition are mostly rejected.

[14]We used the term "profit" assuming two important conditions. The first is that the observed price P_i^* results from a non-cooperative Nash equilibrium à la Bertrand, considered by all players as given in the short run. The second is to assume linear tax rates. We discussed in detail the first one in Appendix B which is the most restrictive

[15]The linear valuation function for profit corresponds to a first-order Taylor approximation of the logarithm of a scaled Cobb-Douglas function (see Appendix C).

In this specification, we assume that physicians value the gross average revenue per consultation (R) and the volume of consultations (D) differently. This assumption appears to be consistent for the markets of physicians in which most physicians work near or at full capacity (see Siciliani et al. (2014)). Given the characteristics of the CAS described above, R depends on the variables V_i, which are directly influenced by i's choice to adopt the CAS, but not by the pricing scheme of other physicians. V_i are thus *payoff shifters* in the sense given by Bajari, Hong, Krainer & Nekipelov (2010). In contrast, D is influenced by both i and j' choices, as well as exogenous variables (Z_i) that describe the local market, ie demand shifters (Jia 2008).

Free-billing physicians can offer their services at two different prices: the regulated fee $\overline{P}$, which is mandatory for low-income[16] patients, and their free-billing prices P_i^*. We assume that the distribution of patient types is exogenous [17].Under these assumptions, the gross average revenue per consultation for physician i can be expressed as:

$$R(V_i(y_i)) \equiv \delta_i \overline{P}(y_i) + (1-\delta_i)P_i^*(y_i) \tag{2}$$

where δ_i represents the exogenous share of consultations realized at the regulated fee. Both $\overline{P}$ and P_i^* are directly influenced by physician i's choice of pricing scheme.

The first impact of the CAS is on the gross fee per consultation conducted at the regulated price.Specifically,

$$\overline{P}(y_i) = (1+\theta y_i) \times \overline{P}_F,$$

where $\theta > 0$ represents the gain related to (i), the increase in fees for consultations conducted at the regulated fee, and (ii) the absence of a social security contribution. $\overline{P}_F$ corresponds to the regulated fee for free-billing physicians[18].

The second impact is on the gross revenue per consultation realized at the free-billing price, which is influenced by the price ceiling imposed by the CAS. This is expressed as:

$$P_i^*(y_i) = y_i \times \min\{P_i^*, 2\overline{P}_R\} + (1-y_i) \times P_i^*,$$

where $P_i^* \equiv P_i(0)$ represents the short-term exogenous free-billing price set by the physician i (justification for this assumption is detailed in Appendix B). $2\overline{P}_R$ denotes the "100%-ceiling" price under the CAS, while $\overline{P}_R$ refers to the regulated fee for consultations for both CAS and regulated fee physicians. Note that if $P_i^* \leq 2\overline{P}_R$, that is, if the physician i has a relatively low free-billing price, it is straightforward to show that $R(1) \geq R(0)$. Consequently, in the absence of spatial competition or a preference for conformity, or if physicians are isolated within both layers of the multiplex network, they would opt for the CAS as long as $R(1) \geq R(0)$.

[16]In France, people benefiting from CMU-C or ACS status.

[17]This notably implies that patients' types are private information, unknown to the physician when a patient books an appointment. Additionally, low-income patients are assumed to be indifferent between physicians since they always pay the same fee, regardless of the physician's pricing scheme.

[18]The basic consultation fee for a free-billing physicians was 23 euros. In the case where the patient was sent by a GP, this price increased to 25 euros. The basic consultation fee for regulated fee physicians was 28 euros.

In addition, physicians can be viewed as firms competing for demand (patients) within a specified market. In a competitive environment with heterogeneous firms (Alderighi & Piga 2012), the demand directed towards firm i is influenced by both market and individual characteristics (Z_i) as well as the price differential between firm i and its competitors. In France, the price paid by patients is the difference between the gross fee per consultation and the reimbursement provided by the NHI. Since P_i^* is fixed in the short term, a physician can only influence the net price paid by patients through the selection of a pricing scheme. As previously noted, adopting the CAS effectively reduces the net price paid by patients by enhancing reimbursements from social security and private insurance, consequently increasing demand.

We define the demand faced by physician i as:

$$D(y_i, Z_i, W_i^{CF}, W_i^{CFR}, p) \equiv \gamma(y_i) \left[N(Z_i) + \eta_1 W_i^{CFR} \mathbf{1_m} y_i + \eta_2 W_i^{CF} (y_i \mathbf{1_n} - p) \right] \tag{3}$$

$\gamma(y_i) > 0$ represents the average number of consultations per patient. The term $N(Z_i) \equiv Z_i \Phi$ denotes the number of patients the physician i has before the game takes place, which is solely dependent on the exogenous market and individual characteristics Z_i. These characteristics include (among others) the number of physicians operating in the same market as the physician i, the price difference between the physician i and competitors or her seniority, and are associated with a vector of parameters Φ. The second term in the square bracket, $\eta_1 W_i^{CFR} \mathbf{1_m} y_i$ is not inherently strategic, as it is independent of other players' strategies, but it allows the stock of patients for a free-billing physician to depend on their proximity to regulated physicians, measured by $W_i^{CFR} \mathbf{1_m}$. W^{CFR} is constructed similarly to W^{CF} and summarizes the number and proximity of regulated physicians that compete in space for patients with free-billing physicians. In fact, if a free-billing physician adopts the CAS, the costs borne by their patients become closer to those of the regulated physicians, potentially allowing the free-billing physician to attract some patients away from the regulated physicians. The last term, $\eta_2 W_i^{CF} (y_i \mathbf{1_n} - p)$ captures the potential poaching (loss) of patients from (to) other free-billing physicians. For isolated physicians, $W_i^{CF} \mathbf{1_n} = 0$ and choosing CAS or not does not produce competitive interactions through η_2. Similarly, if the physician i selects the CAS but all her free-billing competitors also adopt it, we assume that patients associated with free-billing physicians have no incentive to switch physicians.

We expect the parameters η_1 and η_2 to be positive, indicating the poaching of patients from nearby free-billing and regulated physicians when a physician adopts the CAS. They measure the positive extensive margin effect of the CAS. Without loss of generality, we normalize $\gamma(0) = 1$ so that $\gamma = \gamma(1) - \gamma(0) = \gamma(1) - 1$ represents the change in the average consultation per patient associated with the adoption of CAS. This captures the intensive margin effect of adopting the CAS. Note that if physician i does not adopt the CAS pricing scheme, but all her free-billing competitors do, she would lose $\eta_2 W_i^{CF} \mathbf{1_n}$ demand at the extensive margin but would maintain her demand at the intensive margin as $\gamma(0) = 1$. Even if we do not impose a specific sign for γ, the rational behavior of patients dictates that the number of consultations under CAS cannot be lower than that under the free-billing system, i.e., $D(1, Z_i, W_i^{CF}, W_i^{CFR}, p) \geq D(0, Z_i, W_i^{CF}, W_i^{CFR}, p)$. Under this assumption, if $\gamma < 0 \leftrightarrow 0 < \gamma(1) < 1$, we expect, for non-isolated physicians, $|\gamma| < \frac{\gamma(1)\eta_2 W_i^{CF} \mathbf{1_n} + \gamma(1)\eta_1 W_i^{CFR}}{N(Z_i) - \eta_2 W_i^{CF} p}$, where $|\gamma|$ is expected to be small. This is because the gain in patients at the extensive margin for non-isolated physicians, η_2, is anticipated to be relatively minor compared to the total number of patients $N(Z_i)$, such that $N(Z_i) - \eta_2 W_i^{CF} p > 0$. Thus, while we expect γ to be positive, our structural model also accommodates a small loss of demand at the intensive margin.

3.2 The deterministic social utility

The literature on peer effects (Jackson & Zenou 2015) identifies two main mechanisms and their corresponding functional forms for social interactions: the conformity effect, where $S = -\frac{\lambda}{2}(y_i - \bar{y}_{-i})^2$, and the spillover effect, where $S = \lambda y_i \bar{y}_{-i}$, with $\bar{y}_{-i}$ representing the social norm for the player i. Although both effects lead to similar econometric specifications and do not directly influence individual actions, they significantly impact social externalities (i.e., the influence of i's actions on the social norms of peers and subsequently on their strategies) and the welfare properties of these games (Ushchev & Zenou 2020, Boucher et al. 2024).

In this paper, we assume that social interactions are primarily driven by conformity preferences. Several factors lead us to favor this assumption over spillover preferences. Notably, we identified several articles authored by officials from physicians' unions highlighting various "risks" for free-billing physicians considering the adoption of the CAS. Key arguments against the CAS include: (i) the emergence of competition for patients, (ii) constraints on both activity and revenue, and (iii) a potential loss of professional autonomy. A low adoption rate of the CAS may indicate that physicians' conformity preferences are driven by a desire to maintain the status quo and avert the development of more competitive markets, which could result in patient poaching and a decline in prices.

Furthermore, a study on the pricing behavior of free-billing physicians in France by Montmartin & Herrera-Gómez (2023) concludes that "physicians operate in markets characterized by weak incentives to compete on quality and potential non-competitive behavior driven by strategic complementarity in prices, which increases with physician density." Specifically, a high degree of strategic complementarity in price-setting behavior leads to a symmetric equilibrium, where all players establish the same price. These findings strongly support the assumption of conformity preferences among physicians. Thus, we set:

$$S(y_i, W_i^{GF}, p) \equiv \mathbb{1}_{W_i^{GF}\mathbf{1}>0} \left\{ -\frac{\lambda}{2}(y_i - \widetilde{W}_i^{CF} p)^2 \right\} \tag{4}$$

where $\widetilde{W}_i^{CF} = \left(\frac{w_{i1}^{CF}}{\sum_j^n w_{ij}^{GF}}, \ldots, \frac{w_{in}^{CF}}{\sum_j^n w_{ij}^{GF}} \right)$, $n \times 1$ vector, is the i^{th} row of the row-normalized version of W^{GF}, such that $\widetilde{W}_i^{CF} p$ is the average CAS take-up among i's social peers.

3.3 The decision rule and the Bayesian Nash equilibrium

The best response of physician i in the action space, given the expected choices of other physicians, can be represented as:

$$\begin{cases} y_i & = 1 \qquad \text{if } y_i^* > 0 \\ y_i & = 0 \qquad \text{if } y_i^* < 0 \end{cases} \tag{5}$$

where $y_i^* = U^e(1) - U^e(0)$ denotes the difference between the expected utility that physician i derives from choosing $y_i = 1$ compared to choosing $y_i = 0$:

$$\begin{aligned} y_i^* &= \alpha \underbrace{\left[\theta\delta_i\overline{P}_1 - (1-\delta_i)g(P_i)\right]}_{\Delta R = R(1)-R(0)} + (1-\alpha) \underbrace{\left[Z_i\Psi + \rho_1 W_i^{CFR}\mathbf{1_m} + \rho_2 W_i^{CF}(\mathbf{1_n} - p) + \eta_2 W_i^{CF}\mathbf{1_n}\right]}_{\Delta D = D(1)-D(0)} \\ &\quad + \underbrace{\lambda W_i^{GF}\left(p - \frac{1}{2}\mathbf{1_n}\right)}_{\Delta S = S(1)-S(0)} - \varepsilon_i \\ &= \alpha\theta\delta_i\overline{P}_1 - \alpha(1-\delta_i)g(P_i) + (1-\alpha)\left[Z_i\Psi + \rho_1 W_i^{CFR}\mathbf{1_m} + \rho_2 W_i^{CF}(\mathbf{1_n} - p) + \eta_2 W_i^{CF}\mathbf{1_n}\right] \\ &\quad + \lambda W_i^{GF}\left(p - \frac{1}{2}\mathbf{1_n}\right) - \varepsilon_i \end{aligned} \tag{6}$$

where $g(P_i) = \max\{0; P_i^* - 2\overline{P}_R\}$, $\Psi = \gamma\Phi$, $\rho_1 = \eta_1\gamma(1)$, $\rho_2 = \eta_2\gamma$, $\gamma = \gamma(1) - \gamma(0) = \gamma(1) - 1$ and $\varepsilon_i = \varepsilon_i(0) - \varepsilon_i(1)$. Equation (6) highlights key characteristics of individual and networks that increase the likelihood of adopting the CAS. The proportion of consultations conducted at regulated fees (δ_i) enhances the probability of adoption, while a free-billing price exceeding the price ceiling ($g(P_i) > 0$) diminishes it. Interestingly, incentives to adopt the CAS decline with the expected distance-weighted average adoption by competitors ($W_i^{CF}p$), as this reduces the potential gain in activity. Conversely, incentives to adopt the CAS improve with the expected average adoption among peers ($W_i^{GF}p$).

The best responses can be expressed compactly in the strategic space as conditional choice probabilities as:

$$p_i = \Pr[y_i = 1] = F_\varepsilon\left(X_i\beta - \rho_2 W_i^{CF}p + \lambda W_i^{GF}p\right)$$

where $F_\varepsilon(.)$ is the cumulative distribution function (cdf) of ε, $X_i = (\delta_i\overline{P}_R, -(1-\delta_i)g(P_i), Z_i, W_i^{CFR}\mathbf{1_m}, W_i^{CF}\mathbf{1_n})$ and $\beta = (\alpha\theta, \alpha, (1-\alpha)\Psi, (1-\alpha)\rho_1, (1-\alpha)\eta_1)$. The consistent rational expectations equilibrium is defined as a vector $p^* = (p_1^*, ..., p_n^*)$ such that, for all physicians $i \in \mathcal{N}$:

$$\begin{aligned} p_i^* &= F_\varepsilon\left(X_i\beta - \rho_2 W_i^{CF}p^* + \lambda W_i^{GF}p^*\right) \\ &= F_\varepsilon\left(p^*, X_i, W_i^{CF}, W_i^{GF}; \kappa\right) \end{aligned} \tag{7}$$

where the vector of parameters κ is defined as $\kappa \equiv (\beta, \rho_2, \lambda)$. The existence of an equilibrium for the system of equations (7) is guaranteed by the Brouwer fixed-point theorem. However, multiple equilibria may exist. Using a classical contraction mapping argument, we derive a sufficient condition on the values of ρ_2, λ and the row sums of both matrices W^{CF} and W^{GF} that ensures the uniqueness of the equilibrium. Specifically, we assume that the row sums of both are bounded above:

Assumption 3 *The sums of the rows in the competitive layer W^{CF} and the social layer W^{GF} among FB physicians are bounded, such that $||W^{CF}||_\infty \leq c^C$ and $||W^{GF}||_\infty \leq c^G$.*

Note that for a row-normalized matrix such as W^{GF}, $||W^{GF}||_\infty = 1 \implies c^G = 1$, by definition.

Assumption 4 *The strength of competitive and social interactions is bounded above such that $|\,||W^{GF}||\,\lambda - ||W^{CF}||_\infty \rho_2| = |\lambda - ||W^{CF}||_\infty \rho_2| < \frac{1}{\max f_\varepsilon(.)}$*

where $f_\varepsilon(.)$ is the probability density function of ε and the equality holds because W^{GF} is a row-normalized matrix. In the literature on binary choice, three main probability distributions are considered. A majority of the literature (e.g. Brock & Durlauf (2001), Bajari, Hong, Krainer & Nekipelov (2010), Lee et al. (2014)) assumes that ε follows a standard logistic distribution[19]. In this case, Equation (7) is a logit model with $\frac{1}{\max f_\varepsilon(.)} = 4$. Similar quantitative results would be obtained assuming that ε_i follows the standard normal distribution. In this case, Equation (7) is a probit model and $\frac{1}{\max f_\varepsilon(.)} = \sqrt{2\pi} \approx 2.5$. Finally, in a recent article, Boucher & Bramoullé (2022) assumes that ε_i follows a uniform distribution over $[-1/2; 1/2]$. In this case, Equation (7) corresponds to a linear probability model with $\frac{1}{\max f_\varepsilon(.)} = 1$.

Let the fixed-point mapping in Equation (7) be expressed as $\Gamma_n(p) \equiv \Gamma(\kappa, p)$. We show in Appendix D that a unique Bayesian Nash equilibrium exists under Assumption 4:

Proposition 1 *Under Assumptions 3 and 4, $\Gamma_n(p)$ is a contraction mapping, and a unique Bayesian Nash equilibrium (BNE) exists in the game.*

Intuitively, if $\Gamma_n(p)$ is a contraction mapping, then there is a unique fixed point $p^* = \Gamma_n(p^*)$. Since the consistency of rational expectations implies that $p^* = \Gamma_n(p^*)$ if and only if p^* is an equilibrium, the unique fixed point p^* is the unique equilibrium of the game. It is important to note that $\Gamma_n(p)$ being a contraction mapping provides a sufficient condition for the uniqueness of the equilibrium. The assumption 4 is not necessary and is employed here as an empirically tractable sufficient condition. The equilibrium may remain unique even if Assumption 4 is not satisfied (see Section 5.5 in Bhattacharya et al. (2024) for a related discussion).

4 Estimation Strategy and Identification

4.1 Estimation Strategy

The parameters κ in Equation (7) that generate the equilibrium observed in the data can be estimated using a sequential pseudo maximum likelihood estimator (MLE), also known as nested pseudo likelihood (NPL)

[19] This assumption implies that the errors $\varepsilon_i(y_i)$ are independent and extreme-value distributed such that the differences in the errors are logistically distributed. Discussions of the various motivations for logistic distribution are discussed in McFadden (1984), Anderson et al. (1992).

estimator (Aguirregabiria & Mira 2007). This estimator has been successfully applied to estimate models of peer effects with rational expectations (Lin & Hu 2024, Guerra & Mohnen 2022). To motivate the NPL estimator, we first discuss the one-step MLE. Note that under Assumption 2, rational expectations depend only on the information set $\mathbb{I} = \{V, Z, W^{CF}, W^{CFR}, W^{GF}\}$, that is, the strategic decisions of the peers of player i do not affect rational expectations of player i. By mutual independence, the strategic decisions of player i's peers do not affect y_i, and the individual contributions of each player to the global likelihood are independent. The conditional likelihood of an observed action profile y is therefore the product of the likelihoods of the individual strategies y_i for all $i = 1, \ldots, n$, given the information set. The conditional log-likelihood function of the observed action profile y, given the rational expectations equilibrium p^*, is thus expressed implicitly as $\mathcal{L}_n(\kappa; p^*) \equiv \mathcal{L}_n(\kappa; y_i|\mathbb{I})$:

$$\begin{aligned}\mathcal{L}_n(\kappa; p^*) &= \ln\left(\prod_i^n (p_i^*)^{y_i}(1-p_i^*)^{1-y_i}\right)\\ &= \sum_i^n \left\{y_i \times \ln\big(p_i^*\big) + (1-y_i)\times \ln(1-p_i^*)\right\}\end{aligned} \tag{8}$$

Let $\mathcal{K}$ be the support set of κ. The one-step MLE is $\hat{\kappa}_{MLE} = \text{argmax}_{\kappa\in\mathcal{K}}\mathcal{L}_n(\kappa; p^*)$ s.t. $p^* \equiv \Gamma(\kappa, p^*) = F_\varepsilon\left(p^*, X_i, W_i^{CF}, W_i^{GF}; \kappa\right)$, as defined in Equation (7). However, we do not observe the equilibrium rational expectations p^* in the data. To circumvent this issue, we replace p^* with an arbitrary vector p to compute the conditional pseudo log-likelihood $\tilde{\mathcal{L}}(\kappa; p)$ below:

$$\tilde{\mathcal{L}}_n(\kappa; p) = \sum_i^n \left\{y_i \times \ln(p_i) + (1-y_i)\times \ln(1-p_i)\right\} \tag{9}$$

Let $\tilde{\kappa}_n(p) = \text{argmax}_{\kappa\in\mathcal{K}}\tilde{\mathcal{L}}_n(\kappa; p)$ and $\Gamma_n(p) \equiv \Gamma(\tilde{\kappa}_n, p)$. Following Aguirregabiria & Mira (2007), we define a NPL fixed point as a pair (κ, p) s.t. $p = \Gamma_n(p)$ and the set of NPL fixed points as $\Lambda_n \equiv \{(\kappa, p) \in \mathcal{K}\times\mathcal{P} : \kappa = \tilde{\kappa}_n(p), p = \Gamma_n(p)\}$. The NPL estimator is then $(\hat{\kappa}_{NPL}, \hat{p}_{NPL}) = \text{argmax}_{(\kappa,p)\in\Lambda_n}\tilde{\mathcal{L}}_n(\kappa; p)$. Sequential estimation begins with a guess of the equilibrium of rational expectations $\hat{p}^{(0)}$ to estimate $\hat{\kappa}^{(1)} = \text{argmax}_{\kappa\in\mathcal{K}}\tilde{\mathcal{L}}_n(\kappa; \hat{p}^{(0)})$. Using $\hat{\kappa}^{(1)}$, we update the fixed point as $\hat{p}^{(1)} = \Gamma_n\left(\hat{\kappa}^{(1)}, \hat{p}^0\right)$, which is then substituted into the pseudo log-likelihood function to obtain updated estimates of the parameters $\hat{\kappa}^{(2)} = \text{argmax}_{\kappa\in\mathcal{K}}\tilde{\mathcal{L}}_n(\kappa; \hat{p}^{(1)})$. This sequence is repeated until convergence, that is, $\left|\left|\hat{p}^{(k+1)} - \hat{p}^{(k)}\right|\right| < c$ or $\left|\left|\hat{\kappa}^{(k+1)} - \hat{\kappa}^{(k)}\right|\right| < c$, with c a tolerance value sufficiently close to zero, in which case $\kappa^{(k+1)}$ maximizes the pseudo log-likelihood and $\hat{p}^{(k+1)}$ is, by construction of the NPL estimator, a fixed point satisfying the rational expectations assumption. As observed by Aguirregabiria & Mira (2007), convergence to a fixed point is not theoretically guaranteed, although simulations by the authors and empirical evidence in the literature (e.g. Lin & Xu (2017)) show convergence with any starting values of $p^{(0)}$, especially if the fixed point mapping is a contraction. In addition, Kasahara & Shimotsu (2012) develop a relaxation method of the NPL estimator that helps convergence when the fixed-point mapping is not strongly contracting.

Under a set of regularity assumptions, the large sample properties of the NPL estimator, specifically $\sqrt{n}$-consistency and asymptotic normality, are established in Aguirregabiria & Mira (2007), and subsequently adapted in Lin & Hu (2024) for peer effects models. We therefore outline the regularity assumptions and present the resulting proposition, directing the reader to these papers for comprehensive proofs.

Let $\tilde{\mathcal{L}}_i(\kappa; p) = y_i \times ln(p_i) + (1 - y_i) \times ln(1 - p_i)$ be the individual contribution to the pseudo log-likelihood function in Equation (9) and $\tilde{\mathcal{L}}_0(\kappa; p) = \mathbb{E}[\tilde{\mathcal{L}}_i(\kappa; p)]$ such that $\tilde{\kappa}_0(p) = \text{argmax}_{\kappa \in \mathcal{K}} \tilde{\mathcal{L}}_0(\kappa; p)$ and $\Gamma_0(p) \equiv \Gamma(\tilde{\kappa}_0, p)$. Let $\mathcal{P} = [0, 1]^n$ be the support set of p and let κ_0 be the true value of κ.

Assumption 5 *(i) $\mathcal{K}$ is compact, κ_0 is an interior point of $\mathcal{K}$, and $\mathcal{P}$ is a compact and convex subset of $[0, 1]^n$;*

(ii) (κ_0, p^*) is an isolated population NPL fixed point; i.e., it is unique or there is an open ball around it that does not contain any other element of Λ_0;

(iii) The operator $\Gamma_0(p) - p$ has a nonsingular Jacobian matrix at p^*;

(iv) The family $\{L_i(\kappa, p) : \kappa \in \mathcal{K}\}$ is a Vapnik-Cernonenkis class of functions.

(v) The class $\{L_i(\kappa, p, y)\}$ is Donsker with respect to the distribution of X_i for $y = 1$ or $y = 0$, with a square-integrable function.

(vi) $\mathbb{E}\left[|L_i(\kappa, p, y)| \mid \mathbb{I}\right]$ and $|\mathbb{E}\left[L_i(\kappa, p, 1) - L_i(\kappa, p, 0)\right] \mid \mathbb{I}|$ are bounded by a constant.

(vii) There exist nonsingular matrices $\Omega_1(\kappa_0)$ and $\Omega_2(\kappa_0)$ such that:

$$
\begin{aligned}
&-\mathbb{E}\left[\frac{\partial^2 \tilde{\mathcal{L}}(\hat{\kappa}_{NPL}, p^*)}{\partial \kappa \partial \kappa'}\right] \xrightarrow{p} \Omega_2(\kappa_0) \\
&\mathbb{E}\left[\frac{\partial^2 \tilde{\mathcal{L}}(\hat{\kappa}_{NPL}, p^*)}{\partial \kappa \partial \kappa'} + \frac{\partial^2 \tilde{\mathcal{L}}(\kappa_0, p^*)}{\partial \kappa \partial p'} \cdot \left[I - \left(\frac{\partial \Gamma(\kappa_0, p^*)}{\partial p}\right)\right]^{-1} \cdot \frac{\partial \Gamma(\kappa_0, p^*)}{\partial \kappa'}\right] \xrightarrow{p} \Omega_1(\kappa_0)
\end{aligned}
$$

Proposition 2 *If the assumptions 1 to 5 hold, then $\hat{\kappa}_{NPL}$ is consistent, and $\sqrt{n}(\hat{\kappa}_{NPL} - \kappa_0) \xrightarrow{d} \mathcal{N}(0, \Omega_1(\hat{\kappa}_{NPL})^{-1}\Omega_2(\hat{\kappa}_{NPL})\Omega_1(\hat{\kappa}_{NPL})^{-1})$.*

The proof of Proposition (2) is given in detail in Aguirregabiria & Mira (2007) and adapted to peer effect models by Lin & Hu (2024) using the conditional law of large numbers demonstrated by Menzel (2016). The proof can be sketched as follows. The assumptions 5(i) to (iii) ensure $\kappa_{NPL} = \kappa_0$. Assumptions 5(ii) and (iii) are not necessary if the NPL fixed point $\Lambda_0 \equiv \{(\kappa, p) \in \mathcal{K} \times \mathcal{P} : \kappa = \tilde{\kappa}_0(p), p = \Gamma_0(p)\}$ is unique, which typically holds when the fixed point mapping is contracting (Aguirregabiria & Mira 2007). Assumptions 5(iv) to (vi) are regularity conditions on the pseudo log-likelihood function. These are crucial for the application of Theorem 4.1 in Menzel (2016) and ensure that $\tilde{\mathcal{L}}(\kappa_0, p) - \tilde{\mathcal{L}}(\kappa, p)$ converges uniformly in probability to 0 and $\hat{\kappa}_{NPL} \xrightarrow{p} \kappa_0$ (Lin & Hu 2024). Finally, note that the first-order condition of the NPL estimation implies $\frac{\partial \tilde{\mathcal{L}}_n(\hat{\kappa}, \hat{p})}{\partial \kappa} = 0$ and $\hat{p} = \Gamma(\hat{\kappa}, \hat{p})$. By employing a stochastic mean value theorem between (κ_0, p) and $(\hat{\kappa}, \hat{p})$ within the first-order condition and using the consistency condition of the belief system, along with the assumption 5(vii) and the Mann-Wald theorem, we establish the asymptotic normality of the NPL estimator Aguirregabiria & Mira (2007). The NPL estimator is consequently $\sqrt{n}$-convergent, matching the rate of the infeasible MLE estimator. However, due to the fixed-point iteration, the variance of the NPL estimator is increased by $\frac{\partial^2 \tilde{\mathcal{L}}(\kappa_0,p^*)}{\partial\kappa\partial p'} \cdot \left[I - \left(\frac{\partial\Gamma(\kappa_0,p^*)}{\partial p}\right)\right]^{-1} \cdot \frac{\partial\Gamma(\kappa_0,p^*)}{\partial\kappa'}$ compared to the MLE.

Details on the calculation of the estimated variance of the NPL estimator, $\Omega_1(\hat{\kappa}_{NPL})$ and $\Omega_2(\hat{\kappa}_{NPL})$, and of the marginal effects are given in Appendices E and F, respectively.

4.2 Identification

Our reduced-form model is given by:

$$p_i^* = F_\varepsilon\Bigg(\widetilde{\theta}\delta_i\overline{P}_1 - \alpha(1-\delta_i)dP_i + \left[Z_i\widetilde{\Psi} + \widetilde{\rho}_1 W^{CFR}\mathbf{1_m} + \widetilde{\rho}_2 W_i^{CF}(\mathbf{1_n} - p) + \widetilde{\eta_2} W_i^{CF}\mathbf{1_n}\right] \\ + \lambda W_i^{GF}\left(p - \frac{1}{2}\mathbf{1_n}\right)\Bigg) \tag{10}$$

where $\widetilde{\theta} = \alpha\theta$, $dP_i = \max\{0; P_i^* - 2\overline{P}_1\}$, $\widetilde{\Psi} = (1-\alpha)\gamma\Phi$, $\widetilde{\rho}_1 = (1-\alpha)\gamma(1)\eta_1$, $\widetilde{\rho}_2 = (1-\alpha)\eta_2\gamma$ and $\widetilde{\eta_2} = (1-\alpha)\eta_2$, leading to the following structural model (see also Equation (7)):

$$p_i^* = F_\varepsilon\Bigg(\alpha\theta\delta_i\overline{P}_1 - \alpha(1-\delta_i)dP_i + \lambda W_i^{GF}\left(p - \frac{1}{2}\mathbf{1_n}\right) \\ + (1-\alpha)\left[Z_i\Phi(\gamma(1)-\gamma(0)) + \gamma(1)\eta_1 W_i^{CFR}\mathbf{1_m} + \eta_2(\gamma(1)-\gamma(0))W_i^{CF}(\mathbf{1_n} - p) + \eta_2 W_i^{CF}\mathbf{1_n}\right]\Bigg) \tag{11}$$

The threats to identification are twofold. First, some coefficients in the reduced-form model partially capture the effect of several coefficients in the structural model. Second, even if all parameters from the structural model are identified by the estimated reduced-form model, identification may be compromised if distinct sets of parameters produce identical equilibrium strategy profiles.

The one-to-many matching of reduced form with structural coefficients that threatens identification includes $\widetilde{\theta} = \alpha\theta$, $\widetilde{\Psi} = (1-\alpha)\Phi(\gamma(1)-\gamma(0))$, $\widetilde{\rho}_1 = (1-\alpha)\eta_1\gamma(1)$, $\tilde{\rho}_2 = (1-\alpha)\eta_2(\gamma(1)-\gamma(0))$, and $\widetilde{\eta_2} = (1-\alpha)\eta_2$. α is directly identified as the estimated reduced form coefficient associated with $(1-\delta_i)dP_i$, which facilitates the identification of the other parameters (as well as directly identifying $\theta = \frac{\widetilde{\theta}}{\alpha}$), since $(1-\alpha)$ is identifiable. Note that $\gamma(0) = 1$ by definition and that η_2 is directly identified by the reduced-form coefficient associated with $W_i^{CF}\mathbf{1_n}$, $\widetilde{\eta_2} = (1-\alpha)\eta_2 \longleftrightarrow \eta_2 = \frac{\widetilde{\eta_2}}{(1-\alpha)}$. As η_2 is identified, $\gamma(1)$ is straightforwardly identified using the reduced form coefficient associated with $W_i^{CF}(\mathbf{1_n} - p)$, $\widetilde{\rho}_2 = (1-\alpha)\eta_2(\gamma(1)-\gamma(0)) \longleftrightarrow \gamma(1) = 1 + \frac{\widetilde{\rho}_2}{(1-\alpha)\eta_2}$. Finally, the identification of $\gamma(1)$ guarantees the identification of Φ using the relation $\widetilde{\Psi} = (1-\alpha)\Phi(\gamma(1)-\gamma(0)) \iff \Phi = \frac{\widetilde{\Psi}}{(1-\alpha)(\gamma(1)-1)}$, as well as the identification of η_1 through $\eta_1 = \frac{\widetilde{\rho}_1}{(1-\alpha)\gamma(1)}$. Importantly, note that one-to-many matching of reduced form to structural coefficients is possible only if the formers are significantly different from zero. For example, recovering $\gamma(1)$ involves dividing $\hat{\eta}_2$ by $(1-\alpha)\eta_2$, which is not feasible if $\eta_2 = 0$.

We adopt the observational equivalence strategy of Brock & Durlauf (2007) to prove that, as long as the variables are not perfectly linearly dependent, the model is identified, i.e., $p^* = \widetilde{p}^*$ only if $\kappa = \widetilde{\kappa}$, where $\kappa = (\beta, \rho_2, \lambda) = (\alpha\theta, \alpha, (1-\alpha)\Psi, (1-\alpha)\rho_1, (1-\alpha)\rho_2, (1-\alpha)\eta_1, \lambda)$. Let $K = \begin{bmatrix}\delta_i \overline{P}_R & -(1-\delta_i)dP_i & Z & W^{CFR}\mathbf{1_m} & W^{CF}(1-p) & W^{CF}\mathbf{1_n} & W^{GF}(p-\frac{1}{2}\mathbf{1_n})\end{bmatrix}$ denote the $n \times dim(K)$ matrix of variables in the model.

Assumption 6 *(i) K has full rank, i.e. $rank(K) = dim(K)$. (ii) F_ε, the cumulative distribution function of ε is strictly increasing. (iii) $\alpha, \gamma(1), \eta_1, \eta_2 \neq 0$*

The assumption 6 (i) is a classical condition for identification using the observational equivalence approach, which requires the model's variables to be linearly independent and can be empirically tested. In addition, Assumption 6 (i) imposes that there is sample variation in every column of K, especially in the last column of K. In particular, $W^{CF}\mathbf{1}$ must not be a constant, and W^{CF} and W^{GF} must not be linearly dependent. The former is guaranteed if W^{CF} is not row-normalized (or if there is at least one isolated and one non-isolated physician, i.e. $\exists\ i.\ W_i^{CF}\mathbf{1} = 0$ and $\exists\ j.\ W_j^{CF}\mathbf{1} = 1$), and the latter is guaranteed by the construction of W^{CF}, which uses the spatial distance between physicians, and W^{GF}, which is based on administrative boundaries. The assumption 6 (ii) is a technical condition on F_ε, necessary to prove the observational equivalence. Note that Assumption 6 (ii) is satisfied for the cumulative distribution function of the logistic distribution. The assumption 6 (iii) refers to the one-to-many matching of the reduced-form parameters with the structural parameters, which is possible only if some of the former parameters are different from zero.

Proposition 3 *If Assumption 6 holds, then the structural model defined by Equation (7) is identified.*

The proof is given in Appendix G.

5 Data and Descriptive Statistics

5.1 Data collection

Physicians data

The main database utilized in this article was provided by UFC-Que Choisir, the leading French consumer union, which collected information from the French NHI website. This database contains consultation prices (minimum, maximum, and reference prices) for all physicians engaged in private practice across three specializations: ophthalmology, gynecology, and pediatrics in 2016. This unique database also includes information on physicians' gender, practice type[20], pricing schemes, and addresses. We developed a Python program to systematically geolocalize physicians[21].

[20] Their exists four main types in France: only private practice, private and hospital practice, private and salaried practice (outside hospital) and hospital practitioner with a private activity within hospital.

[21] This program used a two step-process with quality scores (from 0 to 1) to find the best geolocalization of each address. First, it computes a quality score using the BAN (Base Adresse Nationale) database, which is the address database officially recognized

Some physicians operate in different locations; therefore, we use their primary place of practice to establish a unique physician-address pair[22]. As physicians do not act as gatekeepers for the three specialties studied, we strongly limit bias related to the choice of the practitioner by patients (linked to professional recommendations and networks). Furthermore, this approach allows us to concentrate on specialties where patient freedom of choice and potential competition among practitioners are highest in France. Our dataset includes the entire population of private physicians, consisting of 2,611 pediatricians (994 are free-billing), 4,611 ophthalmologists (2,660 free-billing) and 5,023 gynecologists (3,055 free-billing).

Local market data

We collect data on the local market from three main databases provided by INSEE (the French National Statistical Office). All data were collected as of December 31, 2015, or January 1, 2016. Two of these databases are part of the Filosofi dataset[23], which offers a variety of socio-economic information on the French population across different geographic levels.[24] The first Filosofi database includes gridded population data at a resolution of 200 meters. The second database provides socio-economic indicators, such as median income, at the IRIS level. IRIS represents districts or segments of municipalities containing approximately 2,000 inhabitants. The third database, "Bénéficiaires du régime général de l'assurance maladie" (Beneficiaries of the General Health Insurance Scheme), contains data at the IRIS level regarding the number of individuals receiving CMU-C, the universal complementary health coverage for low-income populations. Due to statistical confidentiality, this information is not available for certain IRIS. In such instances, missing values were substituted using city-level data.

5.2 Variables and Network construction

Table 2 outlines the variables extracted from the data, as well as those computed to align with the specification presented in Equation (7).

by the administration. For each address with a score lower than 1, the program then asks the OpenStreetMap API to compute a second quality score. The program then compares both scores and uses the highest one. The average quality score obtained is above 98%. For all addresses with a quality score lower than 90%, a manual correction has been implemented using Google Maps.

[22]This step is necessary to build network matrices. As no database was available to automate this process, we manually checked the main practice location of every physician practicing at more than one location using queries on the NHI website: https://annuairesante.ameli.fr/

[23]Also known as Dispositif Fichier Localisé Social et Fiscal in French.

[24]Some data are available at a very fine scale (200-meter grids), while others are aggregated to higher geographic levels to ensure statistical confidentiality.

Model Variable	**Empirical measure**	**Name in tables**	**Sample**
V_i (Endogenous revenue factors)			
SHARE OF REVENUE REALIZED AT REGULATED FEE: $\delta_i \overline{P}_F$	$\hat{\delta}_i$ and $\overline{P}_F$=23 See appendix F for computation of $\hat{\delta}_i$	$\delta_i \overline{P}_F$	FB physicians
SHARE OF REVENUE REALIZED AT A PRICE ABOVE CAS CEILING: $(1-\delta_i)g(P_i^*)$	$(1-\hat{\delta}_i)$ and $\hat{g}(P_i^*) = \max\{0; \hat{P}_i^* - 56\}$ See appendix F for computation of $\hat{P}_i^*$	$(1-\delta_i)g(P_i^*)$	FB physicians
Z_i (Exogenous demand factors)			
PATIENT BASIS (20 KM RADIUS)	1. Population per physician	Pop	All physicians
	2. Median Income	Income	FB physicians
	3. Share of CMU-C patients	CMUC	FB physicians
INDIVIDUAL TRAITS AND PRACTICE	1. Gender (dummy)	Gender	FB physicians
	2. Experience < 4 years (dummy)	New	FB physicians
	3. Multisite practicing	Multisite	FB physicians
	4. Practicing Type	Type	FB physicians
	5. Price difference	Price Gap	FB physicians
W (Network matrices)			
W^{CF} (FB COMPETITION)	$w_{ij}^{CF} = exp(-c_1 * d_{ij})$, $0 < d_{ij} \leq r$	W^{CF}	FB physicians
W^{CFR} (RF COMPETITION)	$w_{ij}^{CFR} = exp(-c_2 * d_{ij})$, $0 < d_{ij} \leq r$	W^{CFR}	All physicians
W^{GF} (SOCIAL)	$w_{ij}^{GF} = 1$ if i and j are in the same NUTS3 region	W^{GF}	FB physicians

Table 2: Correspondence between theoretical and empirical variables

Definition of the multiplex network

To define W^C, the layer of competitive interactions, we must determine two key elements: (i) the weight function, which specifies how geographical distance influences the strength of the link between physicians i and j and (ii) the competitive area for a physician i, defined as a radius that delineates the set of competitors.

For the first point, our choice is based on empirical evidence. In a study of general practitioners (GPs), Lucas-Gabrielli et al. (2016) highlights a convex relationship between distance and the number of consultations. In another study addressing spatial dependence in physician pricing in France, Montmartin & Herrera-Gómez (2023) also employed a convex relationship. Furthermore, Figures H.1 - H.3 in Appendix H illustrate the spatial correlograms of CAS choice and prices across our three specialties. These figures validate the convex relationships for both variables with the distance. These empirical insights lead us to propose the following functions to define competitive weights between physicians:

$$w_{ij}^{CFR} = \exp(-c_1 \times d_{ij}), \quad 0 < d_{ij} \leq r$$
$$w_{ij}^{CF} = \exp(-c_2 \times d_{ij}), \quad 0 < d_{ij} \leq r$$

where d_{ij} represents the distance in km between physician i and j, c_i are the convexity parameters, and r is the radius (in km) defining the competitive area. We consider different convexity parameters since the competition between free-billing physicians and between free-billing physicians and regulated-fee physicians is likely to be heterogeneous.[25] Note that specifying spatial weights as an exponentially decreasing function of spatial distance is usual in the spatial econometrics literature, as well as in more general applications (e.g. Degryse & Ongena (2005), Pinkse et al. (2002)).

For the second point, we determine the optimal radius r using a data-generating process (DGP)-based method. Specifically, we estimate our reduced-form model for each integer value of r from 1 to 20 and select the value that maximizes the log-likelihood. The maximum threshold distance of 20 km (as the crow flies) corresponds, on average, to between 45-60 minutes of driving time, consistent with observed patient referral patterns[26]. Additionally, we introduce an exclusion restriction to the network matrix of competition, ensuring that no competitive interactions are modeled between physicians working in the same medical office[27]. This restriction is based on the assumption that poaching between colleagues sharing the same office is highly unlikely. Instead, we treat such groups as coalitions that pursue common goals.

To define W^G, the layer of social interactions, we use the administrative NUTS3 areas (*départements*). In this context, a physician i is connected to all other physicians practicing within the same NUTS3 area, with each link assigned equal weight. This choice is motivated by three key considerations. First, the use of administrative areas provides exogenous social interactions that significantly differ from competitive interactions regarding both weights and connected nodes. As defined in Assumption 6, our structural model is not identified if the competitive and social layers are linearly dependent. Second, NUTS3 regions are critical administrative units in France, legally recognized for their role in enhancing access to care and public health. As discussed in Borgetto & Lafore (2018) or Donier (2015), NUTS3 regions serve as the primary administrative level for social and medico-social actions[28]. Third, multiple institutions representing physicians are organized at the departmental level. For instance, the Order of Physicians functions as a professional, administrative, and regulatory body at this level, alongside various physicians' unions. These institutional structures, coupled with local policies, are likely to reinforce social interactions among physicians practicing within the same department.

An important concern regarding both layers of the multiplex network is the sorting issue; physicians' decisions about their practice location may reflect both the competitive landscape and the adoption of the CAS (local social norm) across various potential locations. Our database was collected three years after the

[25] Out of curiosity, we performed a spatial correlation analysis using the full sample of physicians, assuming that all regulated-fee physicians adopted the CAS (available upon request). We obtain similar convex relationships across specialties compared to those presented in Appendix H, but with significantly higher convexity—approximately twice as high.

[26] A study conducted by the French Research Institute on Health Economics (IRDES) regarding patients' referral areas and consultation patterns (Barlet et al. 2012) showing that in 2010, 94% and 95% of ophthalmologist and gynecologist consultations, respectively, occur within a driving time of less than one hour for patients.

[27] Note that a significant proportion of physicians share medical offices: approximately 23% of pediatricians, 32% of ophthalmologists, and 36% of gynecologists.

[28] The departmental councils manage vaccination policies, maternal and child protection services, and authorizing the creation and management of certain social and medico-social establishments, including those for dependent elderly people

CAS's implementation in 2013. After installation, physicians' mobility tends to be low as they rely heavily on their patient base. Consequently, only younger physicians with less than four years of experience (which represents the average time from graduation to the first installation in a private office) might have made an endogenous location choice, constituting 17% of our sample. To address this concern in our empirical analysis, we include a dummy variable to identify young physicians.

Variables in V_i and Z_i

We detail in Appendix I our methodology for measuring the endogenous revenue variables, utilizing comprehensive pricing data from physicians. Specifically, we focus on δ_i - the proportion of consultations conducted at the regulated fee - and P_i^* - the free-billing physician price. In summary, we leverage diverse pricing information associated with physician consultations (including reference price, lowest, and highest prices) alongside the proportion of consultations performed at the reference price.

In our framework, the level of activity for the physician i is determined in the short term by exogenous demand factors, as well as individual traits and practice characteristics Z_i. To construct individual measures for the patient base, we calculate the average patient population per physician, the median income, and the proportion of CMUC-C patients within a 20 km radius of the physician's location, utilizing fine-grained data (as detailed in Section 5.1 - Local Data).

For individual traits and practice variables, multisite practice denotes the number of diverse locations where the physician i operates. The type of practice signifies the physician's status, which can be classified into four categories: the purely 'liberal' status (Type 0) and the 'hospital practitioner' status (Type 1), which includes hospital-employed physicians engaging in liberal practice within the hospital. The "Liberal & Hospital" (Type 2) status represents physicians who divide their time between private practice and hospital work. The "Liberal & Employed" (Type 3) status refers to physicians partially employed in private healthcare institutions. Finally, the price difference represents the gap between the physician's reference price and the average weighted reference price (by distance) of its competitors. We use the same competitive network as for W^{CF} in terms of nodes (based on the optimal radius). Correlograms of prices presented in Appendix G also highlight a convex relationship with distance but with a different convexity parameter such that $w_{ij}^P = \exp(-c_3 \times d_{ij})$ with $W^P = \{W_{ij}^P : i \in \mathcal{N}, j \in \mathcal{N}\}$, a $n \times n$ matrix.

Normalization of networks and convexity parameters

Normalization of the network matrices is important empirically, as constraints on their infinity norms guarantee the uniqueness of the equilibrium (Assumption 4). Most empirical studies use a row normalization as it simplifies uniqueness (or stability) conditions by imposing the maximum row sum to be unity.

As discussed in Kelejian & Prucha (2010), this type of normalization does not involve a single normalization factor but instead uses a distinct factor for the elements of each row. Consequently, it alters the proportions of connectivity strengths across units compared to unnormalized weight matrices, which is not theoretically justified for distance-based matrices. Given that spatial competition inherently relies on distance, we adhere to Kelejian & Prucha (2010) and utilize a single normalization factor based on sample size for our competitive layer network (W^{CF} and W^{CFR}). In contrast, for the layer of social interactions (W^P), which does not depend on spatial distance, we implement classical row normalization, ensuring each individual's influence is evaluated relative to their peers. Finally, for the computation of the individual price gap involving W^P, we also use row normalization; we aim to measure the difference between an individual's price and the weighted average price of its competitors, independent of the number of competitors.

The determination of convexity parameters for W^{CF}, W^{CFR}, and W^P is a sensitive task. As discussed in Appendix H, the accurate estimation of these parameters for a binary outcome is not feasible. Consequently, we adopted a cautious approach that involves comparing spatial correlograms for price (which is accurately measurable) and CAS choice (which is less accurately measurable). The values and justification for the convexity parameters utilized in our empirical baseline model for these three matrices are presented in Table H.1 in Appendix H.

5.3 Descriptive Statistics of the CAS adoption

In this section, we provide a general overview of CAS adoption by specialty. We present descriptive statistics for the main variables used in the empirical analysis, disaggregated by specialty, in Appendix J. Table 3 presents a summary of CAS uptake, conditioned on the average free-billing price ($\hat{P}_i^*$) at both the national level and within the five largest cities in France.

Area	**Take-up**	**Take-up** ($\hat{P}_i^* \leq 56$)	**Average FB Price**
		Pediatricians	
France	35.61%	43.92%	49.9
Paris	7.04%	14%	66.42
Marseille	58.97%	60.53%	44.18
Lyon	7.41%	8.33%	49.06
Toulouse	75%	71.43%	50.83
Nice	26.09%	28.57%	50.9
		Ophthalmologists	
France	9.14%	11.28%	50.55
Paris	1.46%	0%	74.69
Marseille	16%	12.82%	47.55
Lyon	6.67%	8.93%	50.61
Toulouse	12.2%	14.71%	49.67
Nice	21.05%	25%	49.06
		Gynecologists	
France	21.41%	29.94%	57.23
Paris	3.76%	17.78%	78.52
Marseille	42.22%	51.61%	61.57
Lyon	3.85%	5.26%	61.67
Toulouse	12.28%	16.67%	52.97
Nice	46.03%	65.52%	56.45

Table 3: Adoption rates of the CAS in 2016

As indicated in Table 3, the adoption rates remain relatively low, even among physicians who would benefit from a net financial gain (column 3), and these rates vary significantly across locations. More than a third (35.

61%) of pediatricians have opted for the new contract, with only 43.92% of those having a free billing price below the CAS price ceiling. Adoption reflects a minority behavior in Paris and Lyon, with approximately 7% adoption rates, whereas it is predominant in Marseille and Toulouse, where adoption rates surpass 50%. Among ophthalmologists, around 9% have embraced the new contract, with negligible uptake in Paris, reinforcing the notion of adoption as a minority behavior within this specialty. Gynecologists exhibit an adoption rate of 21.41%, with notable spatial disparities. In Nice, and to a lesser extent Marseille, nearly half of free-billing gynecologists have adopted the new contract, while adoption rates in Paris and Lyon are close to negligible. The final column of Table 3 presents the average free-billing price of physicians. Comparing these figures with adoption rates does not reveal a clear relationship. For example, the average free billing price for pediatricians in Lyon and Toulouse is similar, but the adoption rate in Toulouse is ten times higher. Similarly, while the take-up rates for pediatricians and gynecologists in Paris and Lyon are nearly identical, the average free-billing price in Paris is around 30% higher. For ophthalmologists, the adoption rate in Nice is three times that in Lyon, despite similar average free-billing prices.

6 Empirical results and Simulations

6.1 Baseline results per specialty

This section estimates the reduced-form Equation (7) separately for the three specialties, as summarized in Table 4. The radius defining the competition area for each specialty is selected based on model fit comparison (measured through the log-likelihood) across radius values ranging from 1 to 20 km, as detailed in Section 5.2. The primary findings of this selection process are illustrated in Figures K.1 - K.3 of the appendix K. Notably, the optimal threshold identified by our DGP approach is consistent with the empirical spatial concentration of physicians. In Figure K.4 of the appendix K, we compare the spatial concentration of the three specialties with that of schools (from kindergarten to high school) and highlight that pediatricians exhibit the highest concentration, whereas gynecologists demonstrate the lowest concentration.

The results presented in Table 4 highlight the significant heterogeneity in both the coefficient values and their statistical significance, underscoring the need for a specialty-specific approach rather than a pooled analysis. For clarity, we will begin by comparing and discussing the reduced-form estimates across specialties for each variable.

Regarding endogenous profit factors, for all specialties, the share of revenue achieved at the regulated price ($\hat{\delta}_i P_F$) significantly increases the likelihood of adopting the CAS. This effect is particularly pronounced for pediatricians, with a marginal effect 3 to 5 times greater than that observed for the other two specialties. The share of revenue realized at the free-billing price above the CAS ceiling price ($(1 - \delta_i)g(P_i)$) exhibits heterogeneous effects across all specialties. As expected, it decreases the likelihood of adopting the CAS for pediatricians and gynecologists. However, an unexpected positive effect is observed for ophthalmologists. A plausible explanation for this discrepancy lies in the composition of their professional activities: consultations represent a significantly smaller proportion of their total activity compared to the other two specialties[29].

We now turn to the analysis of results for the exogenous demand factors. Regarding the patient base, the population per physician positively influences the likelihood of adopting the CAS for gynecologists; however, it does not have a significant effect on the other two specialties. As expected, patient income reduces the likelihood of adopting the new contract, but this effect is significant only for ophthalmologists and gynecologists. Conversely, the proportion of low-income patients (who consistently pay the regulated price, even to free-billing physicians) does not impact practitioners' decisions, irrespective of specialty. In terms of individual traits and practice characteristics, no significant differences are observed based on the gender of the physicians. Nonetheless, the price gap, the difference between a physician's reference price and the distance-weighted average price of her competitors, significantly decreases the likelihood of adopting the CAS across all specialties. This finding indicates that physicians with higher prices than their competitors are less inclined to adopt the new contract. All other variables exhibit heterogeneous effects depending on the specialty. Pediatricians with less than four years of experience and those who partially practice in public hospitals are less likely to adopt the CAS. For ophthalmologists, practicing at multiple sites diminishes the likelihood of adoption, while holding hospital practitioner status increases it, as expected. None of these traits significantly influence the choices of gynecologists.

We conclude this initial analysis by examining the central focus of this article: the influence of peer interactions. We identify two distinct channels of peer effects: spatial competition and pressure to conform. Within the competitive channel, we further differentiate between competition from regulated-fee physicians ($W_i^{CFR}\mathbf{1_n}$) and competition from free-billing physicians ($W_i^{CF}(\mathbf{1_n} - p)$). Notably, the signs of the estimated coefficients related to competitors' influence and network positioning align with theoretical expectations. Although we find clear evidence that social interactions ($W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$) significantly influence the adoption of CAS, competitive interactions have a limited impact. Specifically, no significant competitive effects are detected for pediatricians and ophthalmologists, regardless of whether the competition originates from free-billing or fee-regulated physicians. However, for gynecologists, we observe significant competitive interactions between free-billing and fee-regulated practitioners, indicating that more intense regulated-fee competition incentivizes free-billing physicians to adopt the CAS. In summary, while a physician's decision is strongly influenced by the anticipated choices of their social peers, it is only marginally affected by the expected decisions of their competitors. This finding supports the notion that the CAS induces limited demand effects through the poaching of patients.

[29] Consultations account for 91.4% of pediatricians' activity, 58.7% of gynecologists' activity, and only 25.1% of ophthalmologists' activity.

Model	Variable	Pedia.	Ophthal.	Gyneco.
Endogenous profit factors (V_i)	$\delta_i P_F$	0.120^{***}	0.049^{***}	0.047^{***}
		(0.018)	(0.011)	(0.009)
		0.021	**0.004**	**0.006**
	$(1-\delta_i)g(P_i)$	-0.058	0.027^{**}	-0.033^{**}
		(0.048)	(0.012)	(0.016)
		-0.010	**0.002**	**-0.004**
Exogenous demand factors (Z_i)				
Patient base (20 KM)	Pop	-0.273	0.857	1.622^{**}
		(0.806)	(0.841)	(0.747)
		-0.048	**0.068**	**0.217**
	Income	-0.181	-2.023^{**}	-2.028^{***}
		(0.598)	(0.818)	(0.617)
		-0.032	**-0.161**	**-0.272**
	CMUC	-0.540	2.995	-0.199
		(3.790)	(3.392)	(2.622)
		-0.095	**0.238**	**-0.027**
Individual traits and practice	Gender	-0.131	0.174	-0.181
		(0.154)	(0.154)	(0.110)
		-0.023	**0.014**	**-0.024**
	Experience	-0.402^{**}	-0.254	-0.163
		(0.191)	(0.222)	(0.136)
		-0.071	**-0.020**	**-0.022**
	Multisite	-0.306	-0.206^{**}	-0.134
		(0.196)	(0.095)	(0.096)
		-0.054	**-0.016**	**-0.018**
	Type1	0.519	0.654^{***}	0.137
		(0.467)	(0.259)	(0.161)
		0.092	**0.05Z**	**0.018**
	Type2	-0.563^{***}	0.211	0.139
		(0.204)	(0.221)	(0.151)
		-0.100	**0.017**	**0.019**
	Type3	-0.240	0.109	-0.179
		(0.241)	(0.270)	(0.203)
		-0.043	**0.009**	**-0.024**
	Price gap	-0.081^{***}	-0.053^{***}	-0.074^{***}
		(0.012)	(0.009)	(0.006)
		-0.014	**-0.004**	**-0.010**
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.405	0.550	1.042^{**}
		(0.288)	(0.379)	(0.534)
		0.072	**0.044**	**0.140**
	$W_i^{CF}(\mathbf{1_n}-p)$	-1.253	-1.001	-0.770
		(1.335)	(2.189)	(0.702)
		0.194	**0.074**	**0.096**
	$W_i^{GF}(p-\frac{1}{2}\mathbf{1_n})$	2.892^{***}	3.788^{***}	2.845^{***}
		(0.478)	(0.605)	(0.455)
		0.448	**0.279**	**0.356**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.153	0.681	0.473
		(1.145)	(2.026)	(0.626)
		0.024	**0.050**	**0.059**
Information and Statistics	N	994	2660	3055
	LL	-462.97	-693.29	-1191.99
	Threshold (Km)	10	20	14
	NUTS3 F.E.	YES	YES	YES

Note: Constant terms are omitted. Standard errors in parentheses. Marginal effects in bold. NPL estimation. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Estimation of the reduced-form baseline model for the three specialties

Note that we estimate a non-linear model; therefore, parameter estimates cannot be directly interpreted. To address this, we also computed the sample average marginal effects of the structural parameters. The marginal effects associated with the social interaction parameter (λ) are estimated at 0.448 for pediatricians, 0.356 for gynecologists, and 0.279 for ophthalmologists. These findings indicate that a 10 percentage point increase in the expected adoption within the social layer raises the likelihood of adopting the CAS by approximately 3 to 4.5 percentage points, depending on the specialty.

As explained in Section 4.2, identifying the structural parameters related to competition requires that the three associated reduced-form parameters (ρ_1, ρ_2, η_2) be significantly different from zero. This condition is not satisfied for any specialty. Consequently, the structural effects of the variables in the demand function (Equation (3)) cannot be identified. Nonetheless, we can compute the structural parameters involved in the revenue and social distance functions. Two structural parameters (α and θ) influence the revenue function, while one parameter (λ) is related to the social distance function. The estimated structural value of α is equal to the opposite of the estimated effect of $(1-\delta_i)g(P_i)$ and the estimated structural value of θ is the ratio between the estimated reduced form effect of $\delta_i P_F$ and α. Finally, the estimated structural value of λ directly corresponds to its estimated reduced-form coefficient. Table 5 below summarizes the identified structural parameters for the three specialties.

Structural parameter	**Pediatricians**	**Ophthalmologists**	**Gynecologists**
α	N/A	-0.027	0.033
θ	N/A	-1.833	1.416
λ	2.892	3.788	2.845

Table 5: Identified structural parameters

For pediatricians, since α is not significant, we are unable to compute θ, resulting in only the identification of the structural effect related to the preference for conformity. For the other two specialties, we can identify the structural parameters associated with the revenue function, but these parameters have opposite signs. For gynecologists, the findings align with expectations: the probability of adopting the CAS increases with the share of revenue generated from the regulated fee and decreases with the share of revenue obtained at a price exceeding the CAS ceiling price. Conversely, the unexpected results for ophthalmologists may be attributed to the previously mentioned issue: consultation activity constitutes only a limited portion of their overall practice, and we do not adequately capture free-billing pricing behavior for this specialty.

Comparison with misspecified models

To illustrate the importance of accounting for the two sources of interactions in physician decisions, we estimate alternative specifications of Equation (7) that include: (*i*) only competitive interactions or (*ii*) only social interactions (columns 4 and 5 in Table 6). For clarity, we report only the reduced-form coefficients related to network interactions in Table 6. The estimated parameters associated with profits and demand factors remain consistent with those presented in Table 4 across the three specifications.

Model	Variable	Baseline	Competition only	Conformity only
		Gynecologists		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	1.042**	1.119***	
		(0.534)	(0.562)	
		0.140	**0.141**	
	$W_i^{CF}(\mathbf{1_n}-p)$	−0.770	−0.543	
		(0.702)	(0.724)	
		0.096	**0.068**	
	$W_i^{GF}(p-\frac{1}{2}\mathbf{1_n})$	2.845***		2.921***
		(0.455)		(0.447)
		0.356		**0.366**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.473	0.253	
		(0.626)	(0.650)	
		0.059	**0.032**	
Information and Statistics	LL	−1191.99	−1197.90	−1195.29
	LR Test		11.81(**0.001**)	6.6(**0.086**)
		Ophtalmologists		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.550	0.557	
		(0.379)	(0.435)	
		0.044	**0.041**	
	$W_i^{CF}(\mathbf{1_n}-p)$	−1.001	−0.854	
		(2.189)	(2.316)	
		0.074	**0.063**	
	$W_i^{GF}(p-\frac{1}{2}\mathbf{1_n})$	3.788***		3.889***
		(0.605)		(0.642)
		0.279		**0.287**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.681	0.531	
		(2.026)	(2.159)	
		0.050	**0.039**	
Information and Statistics	LL	−693.29	−697.17	−694.32
	LR Test		7.76(**0.005**)	2.07(**0.558**)
		Pediatricians		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.405	0.555*	
		(0.288)	(0.337)	
		0.072	**0.088**	
	$W_i^{CF}(\mathbf{1_n}-p)$	−1.253	−1.085	
		(1.335)	(1.441)	
		0.194	**0.171**	
	$W_i^{GF}(p-\frac{1}{2}\mathbf{1_n})$	2.892***		3.242***
		(0.478)		(0.414)
		0.448		**0.508**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.153	−0.013	
		(1.145)	(1.259)	
		0.024	**0.039**	
Information and Statistics	LL	−462.97	−469.36	−468.67
	LR Test		12.776(**0.000**)	11.392(**0.001**)

Note: Constant terms are omitted. Standard errors in parentheses. Marginal effects in bold. NPL estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Estimation of different reduced-form models for the three specialties

Likelihood ratio tests indicate that the baseline model, which incorporates both effects, provides a significantly better fit than the two alternative specifications, particularly when compared to the model that includes only competitive interactions. However, focusing exclusively on social effects (column 5) introduces an upward bias in the estimated taste for conformity (λ). Conversely, the specification with only competitive effects yields downward biased estimates of η_2 and ρ_2 (although these parameters remain insignificant in either specification) and an upward biased estimate of ρ_1.

These findings highlight the necessity of specifying a structural model that incorporates both sources of interactions. A model relying on a single-layered network of interactions would inadequately represent the determinants of physicians' decision.

6.2 Robustness check

Mismeasurement

In Appendix L, we detail the methodology for computing the share of activity realized at the regulated price (δ_i). However, this estimated value is inherently subject to measurement errors. This arises for two main reasons. First, the calculation relies on information regarding various physicians' prices, which is incomplete for a segment of our sample. Second, even when this information is fully available, it yields an imperfect proxy for the true share of activity conducted at the regulated price. It is well known that measurement errors introduce endogeneity, potentially biasing not only the estimated coefficient of the affected variable but also smearing on the other coefficients in the model.

To assess the potential severity of this issue, we generate an alternative estimate of δ_i by introducing a random component to our initial calculation, $\hat{\delta}_i$, representing the measurement error. Specifically, the new measure is calculated as: $\hat{\delta}_i(a) = \hat{\delta}_i + U(0, \overline{\delta})$ where $\mathcal{U}$ is the uniform distribution and $\overline{\delta}$ measures the empirical mean of $\hat{\delta}_i$ at the NUTS3 level. This adjustment intentionally inflates our baseline measure, as existing official data indicate a higher share of activity conducted at regulated prices. The descriptive statistics for the two measures of δ_i are presented in Table 7.

Statistic	**Pediatricians**		**Ophthalmologists**		**Gynecologists**	
	$\hat{\delta}_i$	$\hat{\delta}_i(a)$	$\hat{\delta}_i$	$\hat{\delta}_i(a)$	$\hat{\delta}_i$	$\hat{\delta}_i(a)$
Mean	0.1202	0.2104	0.1071	0.1924	0.1178	0.2134
Min	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000
Q1	0.0000	0.0499	0.0000	0.0452	0.0000	0.0484
Median	0.0000	0.1034	0.0000	0.0943	0.0000	0.1114
Q3	0.1000	0.2379	0.0000	0.2066	0.1000	0.2598
Max	1	1	1	1	1	1

Table 7: Descriptive statistics for different δ_i

We account for substantial potential mismeasurement, as evidenced by the noticeable differences in the distributions of $\hat{\delta}_i$ for the two alternative measures. Table L.1 in Appendix L presents a comparison of the reduced-form estimation results from our model of competitive and social interactions using these two measures of δ_i. The first line displays the results obtained with $\hat{\delta}_i$ (baseline model), while the second line illustrates the results achieved with $\hat{\delta}_i(a)$. The stability of coefficient estimates across specifications indicates that mismeasurement in δ_i is unlikely to introduce significant bias in our results.

Network matrices

Another source of concern is the construction of the matrices representing the two layers of the multiplex network. Although the exclusion restriction conditions imposed on W^{CF} and W^{CFR}, along with the exogeneity of W^{GF}, ensure the identifiability of both competitive and social interactions, an incorrect specification of these interactions—and their associated weights—could introduce bias.

For W^{CF} and W^{CFR}, we highlight in Appendix K the stability of our results when varying the radius used, for a given weighting distance function. However, the true convexity parameter of the weighting distance functions remains unknown, and the empirical results are credible only if they demonstrate stability across different levels of convexity. To assess this, we analyze the sensitivity of our results to variations in the convexity parameter of the weighting distance functions applied to W^{CF} and W^{CFR}. Specifically, we evaluate the robustness of our baseline findings in two respects: (*i*) the optimal radius determined by our DGP-based approach and (*ii*) the consistency of the significance and estimated values of the reduced-form coefficients.

Table L.2 in Appendix L summarizes our findings by comparing key interaction coefficients, log-likelihood, and optimal thresholds from our baseline model with those obtained using higher and lower convexity parameters[30] for W^{CF} and W^{CFR}. For each specialty, the radius that best fits the data remains stable, regardless of the convexity parameters c_1 and c_2 considered.

Regarding the significance and estimated values of the key interaction coefficients, we observe notable stability: the social interaction coefficient is highly significant, whereas the coefficients associated with competitive interactions are not significant. Furthermore, there are only minor differences in terms of goodness-of-fit measures. Lastly, we refrain from presenting the estimated coefficients for the other variables of the model in Table L.2 to avoid overwhelming the discussion. However, these coefficients exhibit stability as well, and complete results are available upon request.

Concerning W^{GF}, we use NUTS 3 regions to define social peers as physicians within the same specialty in a given administrative area. However, this approach may not capture the true social relationships among physicians. Furthermore, we assume uniform weights, positing that each member of i's social network exerts an equal influence on the formation of the norm. In practice, some peers are likely to have a greater impact on the idiosyncratic norm that each physician considers when deciding to adopt CAS.

In France, NUTS 2 administrative regions play a crucial role in organizing healthcare services, with Regional Health Agencies (*Agences Régionales de Santé* ARS) responsible for managing on-call duties and ensuring continuity of care. Utilizing a finer geographical level, such as cities, is less advantageous due to the heightened risk of identification threats stemming from stronger correlations with W^{CF}, the layer of competitive interactions among free-billing physicians.

[30] Specifically, we increment both c_1 and c_2 by ± 0.1.

To assess the robustness of our results, we computed two alternative specifications for the social network. The first uses the administrative level of NUTS 2 to define social relationships with homogeneous weights. The second retains the NUTS 3 administrative level but introduces heterogeneity by assigning peers working in the same office a weight ten times greater than that of other peers in the formation of the norm.

The results, presented in Table I.3 in Appendix L, confirm the validity of our preferred social network specification. When the social network is defined at the administrative level NUTS 2 (see column 4 of Table L.3), we observe considerable variability in the results. For pediatricians, the social interaction parameter is both negative and statistically insignificant, whereas it increases substantially for ophthalmologists, leading to a violation of the sufficient condition for equilibrium uniqueness. In the case of gynecologists, the parameter decreases significantly and also loses its significance. Additionally, employing the NUTS 2 administrative level results in a markedly lower log-likelihood for gynecologists and pediatricians compared to our baseline model.

When heterogeneity in the weights of the social matrix is introduced (column 5), the results remain largely consistent with those obtained using homogeneous weights, albeit with a slightly reduced conformity effect. Nonetheless, the goodness-of-fit diminishes across all specialties when compared to the baseline model.

6.3 Simulations

The influence of price-ceiling on contract take-up

An important feature of the CAS is its price ceiling, which is designed to limit additional fees and enhance financial access to care. Given that 31% of the physicians in our study set reference prices above this threshold, it is crucial to investigate whether modifications to the price ceiling would significantly affect CAS adoption. To explore this, we examine two alternative price-ceiling levels for consultations: 60€ and 80€, in comparison to the current ceiling of 56€ under the CAS.

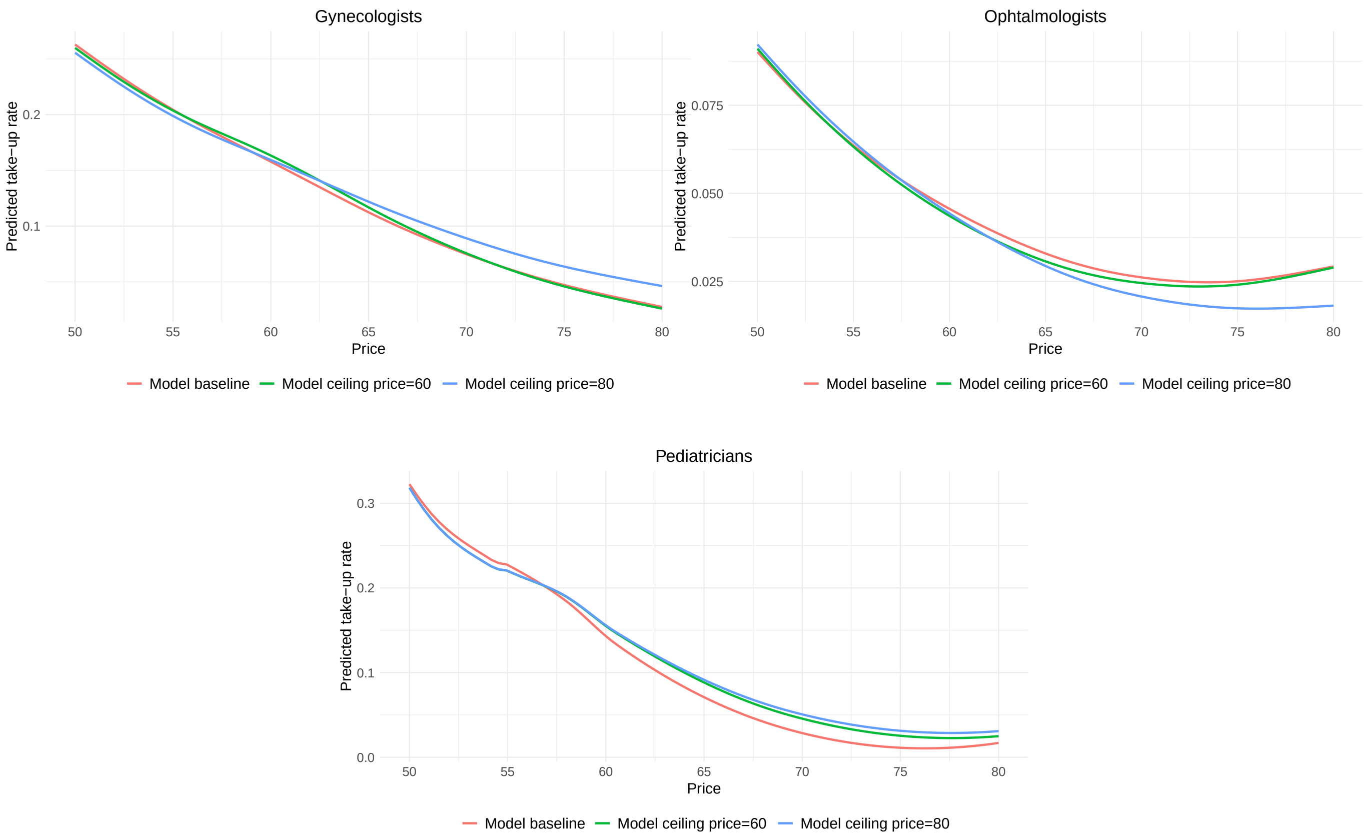

Figure 1: Simulated take-up for different price ceilings

Figure 1 presents the distribution of CAS take-up by reference price in different price ceiling scenarios. While the average take-up rate remains relatively stable, the distribution of adopters by reference price shows significant changes. As illustrated, increasing the price ceiling shifts the take-up distribution to the right for gynecologists and pediatricians, leading to a more balanced take-up rate among free-billing physicians. Conversely, a contrasting trend is observed for ophthalmologists. This divergence occurs due to the estimated price ceiling's effect, which is positive for ophthalmologists but negative for the other two specialties.

Table 8 provides further insight into this redistribution. The take-up rates predicted by the structural model closely align with observed adoption rates; however, some deviations are evident: the model slightly underestimates take-up below the CAS price ceiling and overestimates it above. Our simulations indicate that increasing the price ceiling would lead to a modest increase in the take-up rate among gynecologists and pediatricians whose reference prices exceed the CAS threshold, while slightly reducing it for those with prices below. Conversely, a reverse pattern is observed for ophthalmologists.

This analysis underscores the limited impact of price ceiling levels on CAS adoption rates, regardless of the specialty under examination.

Sample	Subsample	Observed adoption rate ($2\overline{P}_1 = 56$)	Predicted adoption rate ($2\overline{P}_1 = 56$)	Simulated adoption rate ($2\overline{P}_1 = 60$)	Simulated adoption rate ($2\overline{P}_1 = 80$)
Pediatricians	$P_i \leq 2\overline{P}_1$	43.92%	43.08%	42.77%	42.77%
	$P_i > 2\overline{P}_1$	5.16%	8.25%	9.35%	9.34%
Ophthalmologists	$P_i \leq 2\overline{P}_1$	11.28%	10.94%	10.98%	11.05%
	$P_i > 2\overline{P}_1$	2.47%	3.52%	3.38%	3.18%
Gynecologists	$P_i < 2\overline{P}_1$	29.94%	29.76%	29.56%	29.34%
	$P_i > 2\overline{P}_1$	9.49%	9.74%	10.03%	10.33%

Table 8: Observed and simulated take-up for different price ceiling

The influence of interactions on contract take-up

To provide further insight into the impact of interactions, we propose a comparative static exercise in which we simulate the average CAS uptake for alternative values of the two main structural interaction coefficients (η_2 and λ). The values of the other coefficients in the model are set to their estimated values. Regarding social interactions, we examine scenarios where the taste for conformity is either zero or set at its estimated value. For competitive interactions, we investigate combinations of reduced-form coefficients [31] consistent with the empirical estimations obtained. The results are summarized in Figure 2, from which two main observations emerge.

First, in the absence of competitive interactions ($\eta_2 = 0$), which is consistent with our estimations, the predicted take-up is higher in all samples when we assume that the physicians do not have a taste for conformity ($\lambda = 0$) compared to the case where we use the estimated taste for conformity ($\hat{\lambda}$). This difference is particularly pronounced among gynecologists and ophthalmologists. The smaller difference observed for pediatricians is attributed to the notable adoption rate of approximately 36%, which is approaching the 50% threshold, beyond which the taste for conformity increases the likelihood of opting for the CAS.

Specifically, we estimate that nearly 33% of gynecologists would have adopted the CAS in the absence of a preference for conformity, compared to the observed take-up rate of 21%. The difference is even more pronounced for ophthalmologists, where the simulated take-up is over three times higher than the observed rate (30% versus 9%). For pediatricians, the simulated adoption rate exceeds the observed rate (52% compared to 36%). These simulations highlight the adverse impact of physicians' preference for conformity on the average take-up of the CAS, emphasizing its role in limiting the policy's effectiveness in enhancing financial access to care.

Second, the predicted take-up and η_2 are positively correlated. When selecting CAS increases a physician's demand at the extensive margin ($\eta_2 > 0$), the predicted take-up is unambiguously higher than the observed take-up. Conversely, when $\eta_2 < 0$, meaning that opting for the CAS diminishes a physician's demand at the extensive margin (which may occur if it sends a negative quality signal to patients), the predicted take-up may be lower than the observed one only if this effect is sufficiently strong.

[31] More specifically, we test over $\tilde{\eta}_2 \in [-2; 2]$ and $\rho_2 \in [-2; 2]$.

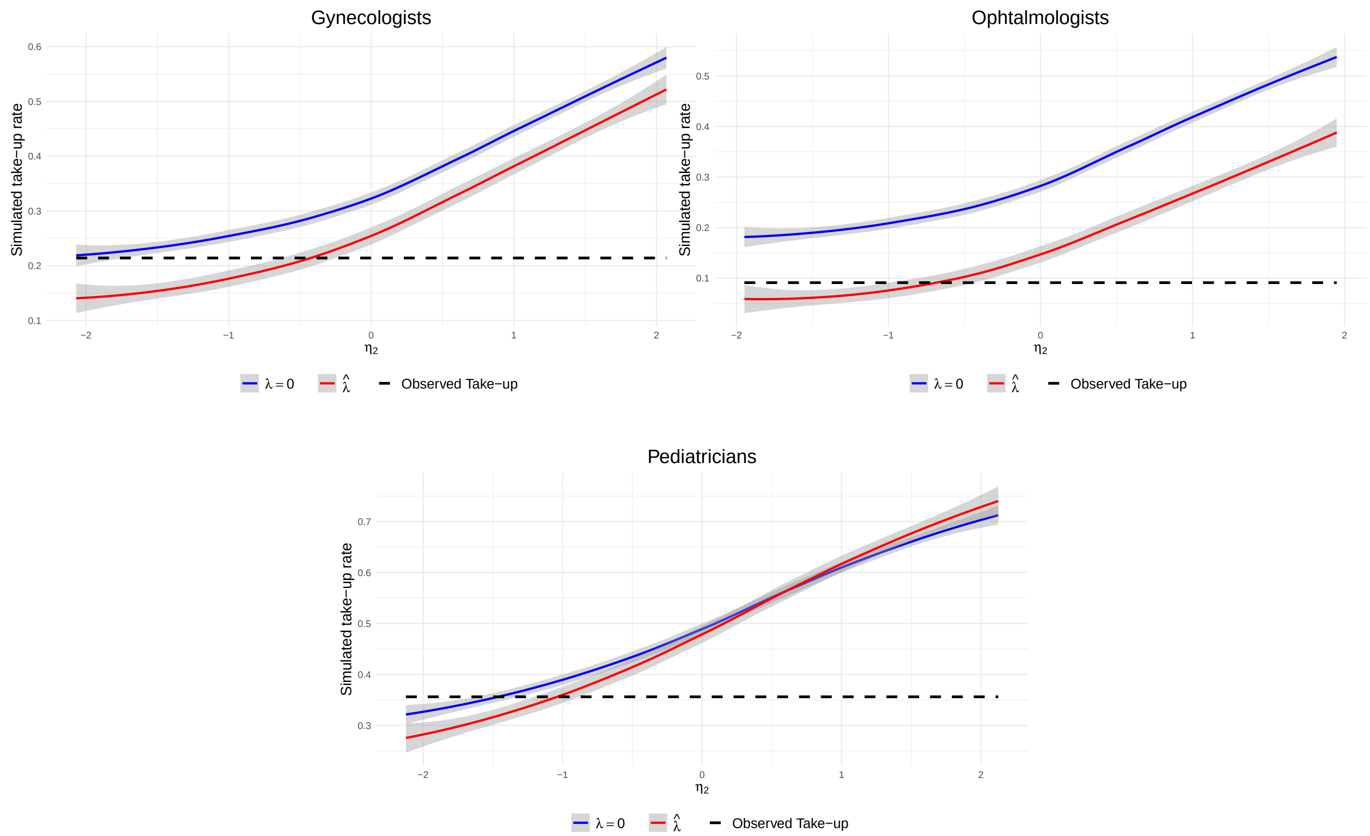

Figure 2: Simulated take-up rates

6.4 Policy design effectiveness

This in-depth empirical analysis of the adoption of CAS allows us to discuss its effectiveness. To be fully effective, the design of such a pricing scheme implicitly assumes that (i) agents respond to financial incentives, (ii) markets are competitive, and (iii) there is no preference for conformity. Our results highlight limited physician responses to the financial incentives offered by CAS, as well as the absence of significant demand changes from the patient's side. Moreover, we identify a strong preference for conformity. Together, these factors largely explain the low rate of CAS adoption and the limited impact of this policy on improving financial access to care. The efficacy of this policy has faced strong criticism in a public report by the Government Accountability Office (Cour des Comptes in French) in 2017. In a specific section of the document titled "Limited Effects at a Considerable Cost" (Cour des Comptes 2017), the institution estimated that to prevent one euro of additional fees, the NHI spent 10 euros in 2015. This estimate integrates all expenditures incurred by the NHI related to CAS incentives for physicians, including increases in regulated fees for certain technical acts and consultations, the payment by the NHI of social security contributions on acts performed at regulated fees, and the authorization for certain regulated-fee physicians (who possess the required qualifications) to opt for the CAS.

In our data, 89.8%[32] of free-billing physicians who adopted the CAS had an average free-billing consultation price at or below the CAS price ceiling of 56 euros. This proportion increases to 94.8% when considering an

[32]This number corresponds to the mean across all specialties. By specialty, 81.5% of gynecologists, 93.4% of ophthalmologists, and 96.9% of pediatricians adopted the CAS with an average free-billing price for a consultation below or equal to the CAS price ceiling of 56 euros.

average free-billing price at or below 60 euros. Consequently, the majority of CAS adopters were able to retain the benefits of the scheme without altering their pricing policy. Moreover, it is plausible that these physicians would not have significantly raised their prices had they remained under the standard free-billing contract.

Among the 1,561 physicians who opted for the CAS in our data, 310 were previously regulated-fee physicians. These physicians represent a specific subset, possessing qualifications — primarily as former academic hospital fellows or clinical instructors (known in French as "chefs de clinique") — which could have allowed them to practice as free-billing physicians; however, they chose to operate under the regulated fee scheme instead. Negotiations between physicians' unions and the NHI during the design of the CAS facilitated their transition to the CAS. For these physicians, the CAS presents an opportunity to increase their earnings, allowing them to charge additional fees without imposing extra costs on their patients. This is feasible because most private insurance contracts cover 100% of the extra fees for CAS adopters (see Section 2 for details). In summary, the CAS did not succeed in lowering the prices charged by free-billing physicians and instead had a counterproductive effect, as 20% of the CAS adopters were former regulated-fee physicians.

Our results also highlight the low sensitivity of physicians' decisions to the financial incentives provided by the CAS, suggesting that increasing the price ceiling would likely not lead to a significantly higher take-up rate. However, other parameters, such as the exemption from social security contributions, may prove to be more effective, as the reduced-form parameter concerning $\delta_i P_F$ is significant across the three specialties. Rather than reimbursing social security contributions for consultations conducted at regulated fee for all CAS adopters, a more efficient approach to enhancing selection on slopes would be to propose a proportional decrease in social security contributions based on the observed reduction in free-billing prices among physicians who have adopted the CAS.

Finally, we demonstrate the importance of taste for conformity in physician decisions, and an appropriate public policy design should take this into account. The adoption of the CAS is voluntary, and a preference for freedom of practice is likely to generate a negative bias toward the CAS, making adoption a minority behavior a priori. In this context, the existence of conformity preferences diminishes overall adoption rates. Conversely, if choosing the CAS were to become the norm, physicians' preference for conformity would likely foster increased adoption. This observation raises important questions about the effectiveness of voluntary incentive policies in the presence of a taste for conformity. Specifically, when adoption is a minority behavior a priori, our analysis suggests that mandating adoption might be a necessary condition for the success of such policy designs.

7 Conclusion

In this paper, we emphasize the significance of peer interactions in physicians' decisions to voluntarily adopt a new pricing scheme intended to halt the continual rise of fees and enhance the affordability of care services for patients. We modeled, through a multiplex network, two distinct sources of peer interaction: spatial competition and a preference for conformity. We identified them using a structural econometric approach combined with a unique geolocalized database that covers the entire population of french private physicians across three medical specialties.

Our results provide two main takeaways for healthcare cost control policy design.

First, the design should be grounded on realistic assumptions regarding the behavior of care providers, which is highly country-specific, since health system organizations are heterogeneous. In France, for instance, powerful physician unions negotiate directly with the NHI and care providers are not allowed to sort patient. Consequently, classical economic mechanisms, such as competition and financial incentives, are unlikely to exert a strong impact. This stands in contrast to a country like the United States, where physician unions wield considerably less power and patient sorting is common practice.

Second, recognizing the various forms of interactions among care providers is crucial for designing effective policies. Our results highlight the presence of strong conformity effects and the absence of spatial competition, which explain in a large extent the low adoption rate of the new pricing scheme both from the perspective of selection on levels and slopes.

Those two elements combined largely explain the social inefficiencies of the program, with an estimated cost of 10€ for every 1€ of extra fees saved. During 2016, due to costs and the low take-up rate of the new pricing scheme, the French government, the NHI, and physician unions entered into new negotiations. It concluded with a revised version of the pricing scheme discussed in this paper, called "Option Pratique Tarifaire Maîtrisée" (OPTAM), which remains in effect in 2025. This updated pricing scheme retains nearly all characteristics of the CAS, with the exception that it is overall more beneficial for physicians. This improvement is achieved through an increase in total benefits, which includes replacing the reduction in social security contributions with a direct bonus provided by the NHI.

This last point highlights some limitations of our paper and the need for more research efforts in analyzing the efficiency of voluntary programs. Due to constraints in data availability, our analysis is limited to a single medical act (consultation) without information on the quantity, thereby assuming that physicians operate at full capacity. It is important to account for the diversity in physicians' practices to more accurately evaluate the impacts of the program's financial incentives. It seems also important to have panel data to be able to model and test the adoption of such a program in a dynamic setting with priors. This would significantly change the rational expectations of players about peers' choice, as well as our understanding on the dynamic influence of both competition and social interactions. With more detailed data on physicians' graduation placements, for example, we could investigate different social layers within the multiplex network, moving beyond conventional administrative boundaries to include aspects such as alumni networks.

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Appendices

A Evidence on the adoption of the CAS

In this appendix, we present descriptive statistics on the adoption of CAS by physicians. The figures below illustrate the non-adoption rate by NUTS3 regions for free-billing physicians whose average free-billing price is below the CAS price ceiling. NUTS3 regions highlighted in light gray indicate areas with no free-billing physicians.

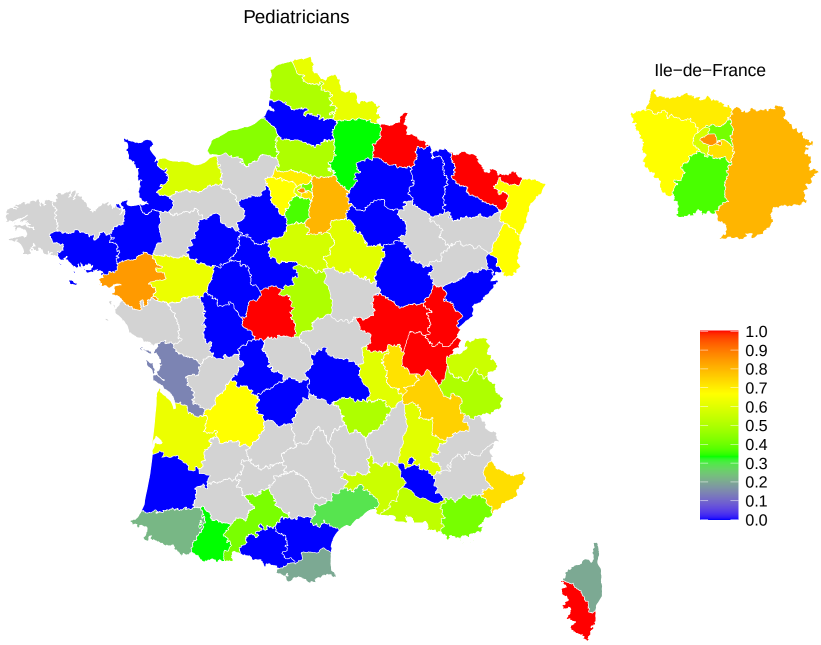


Figure A.1: Non adoption rate of CAS among pediatricians who would financially benefit

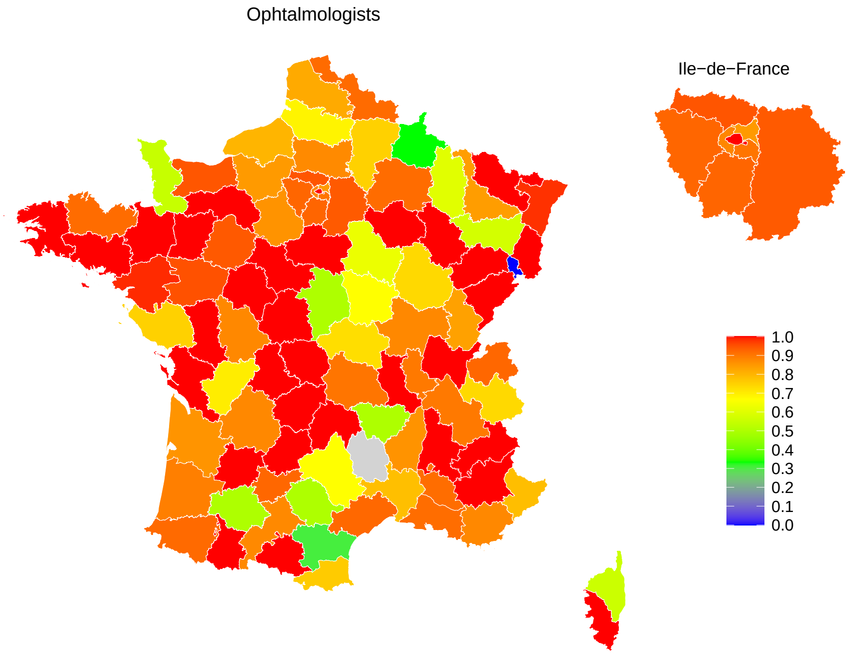


Figure A.2: Non adoption rate of CAS among ophatlmologists who would financially benefit

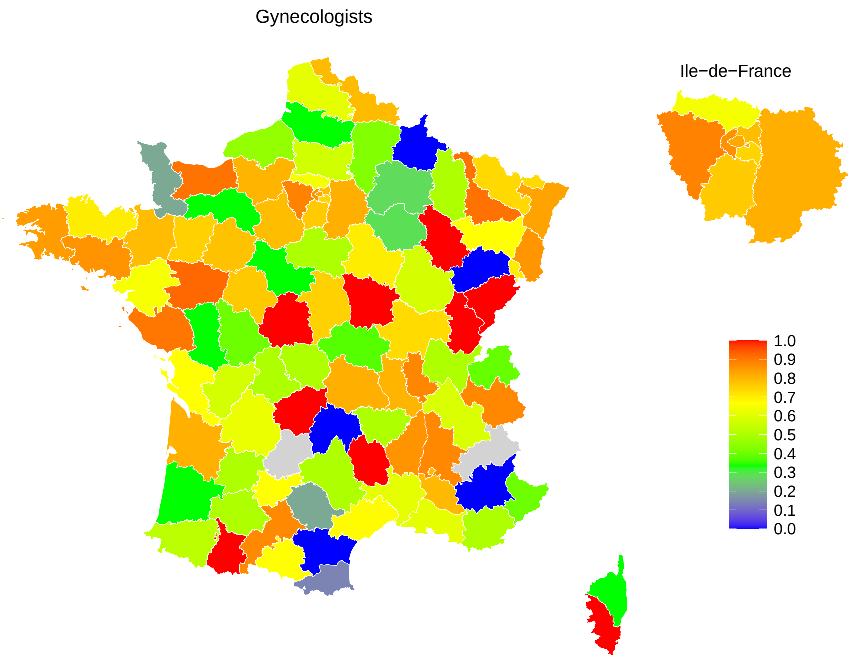


Figure A.3: Non adoption rate of CAS among gynecologists who would financially benefit

The tables below present the correlation matrix illustrating the relationship between the adoption of the CAS and various measures of average peer choices.

	cas	WCASD	WCASM1	WCASM2	WCASM3	WCASM4	WCASM5	WCASM6
cas	1.000	0.320	0.312	0.309	0.325	0.348	0.372	0.361
WCASD		1.000	0.659	0.700	0.712	0.442	0.612	0.698
WCASM1			1.000	0.922	0.837	0.551	0.663	0.689
WCASM2				1.000	0.906	0.515	0.635	0.673
WCASM3					1.000	0.511	0.624	0.671
WCASM4						1.000	0.631	0.554
WCASM5							1.000	0.853
WCASM6								1.000

Table A.1: Correlations between CAS adoption and average choice of peers - Pediatricians

	cas	WCASD	WCASM1	WCASM2	WCASM3	WCASM4	WCASM5	WCASM6
cas	1.000	0.191	0.140	0.160	0.154	0.224	0.183	0.158
WCASD		1.000	0.561	0.614	0.673	0.306	0.529	0.612
WCASM1			1.000	0.855	0.749	0.450	0.557	0.543
WCASM2				1.000	0.852	0.425	0.554	0.549
WCASM3					1.000	0.392	0.538	0.544
WCASM4						1.000	0.510	0.347
WCASM5							1.000	0.761
WCASM6								1.000

Table A.2: Correlations between CAS adoption and average choice of peers - Ophthalmologists

	cas	WCASD	WCASM1	WCASM2	WCASM3	WCASM4	WCASM5	WCASM6
cas	1.000	0.351	0.254	0.311	0.292	0.360	0.405	0.381
WCASD		1.000	0.565	0.662	0.682	0.435	0.621	0.654
WCASM1			1.000	0.812	0.683	0.484	0.595	0.559
WCASM2				1.000	0.840	0.474	0.589	0.575
WCASM3					1.000	0.432	0.548	0.561
WCASM4						1.000	0.629	0.524
WCASM5							1.000	0.869
WCASM6								1.000

Table A.3: Correlations between CAS adoption and average choice of peers - Gynecologists

The average choice of peers uses peer matrices that are defined by nodes (physicians) and weights (strength of the interaction). For simplicity, we consider homogeneous weights (1 if i and j are connected and 0 otherwise) and we row-normalize all peer matrices. Regarding the rules for node definition, we provide a description of the construction of the various peer matrices below:

Definition of W	**Description**
WCASD	Physicians located in the same NUTS3 region
WCAS1	All neighbors within a radius of 5 km
WCAS2	All neighbors within a radius of 10 km
WCAS3	All neighbors within a radius of 20 km
WCAS4	Nearest neighbor
WCAS5	5 nearest neighbors
WCAS6	10 nearest neighbors

Table A.4: Correlations between CAS adoption and average choice of peers

B Justification of the sticky prices assumption

The profit function used in our framework implies two important conditions. First, the observed free-billing price P_i^* arises from a non-cooperative Nash equilibrium à la Bertrand, and is consequently treated as exogenous in the short run by all participants. Second, we assume linear tax rates. This latter assumption is not particularly restrictive, as tax rates and social security contributions for liberal activities generally constitute stable proportions of gross revenue. The former assumption is stronger, as it implies sticky prices and a myopic behavior of the physician concerning the impact of taking up the CAS contract on competitors' prices. However, the specific context of the physician market in France, characterized by significant inertia among participants, alongside empirical evidence, provides compelling support for this assumption in the short run.

We start with some theoretical arguments. Once a physician decides to adopt or not the CAS, competitor reactions in terms of pricing are unlikely to be immediate for several reasons. First, competitors may not possess this information in the short run. Collecting data on a competitor's adoption of the CAS necessitates researching their name on the NHI website. Furthermore, there is a substantial administrative delay between a physician's decision to adopt the CAS and the effective implementation of the new pricing scheme (as well as the corresponding update of the NHI website). Second, physicians may be reluctant to reduce their prices in response to the adoption of CAS by competitors, particularly if the impact on their demand is minimal. Specifically, physicians' demand may be weakly elastic with respect to price due to: 1) an imbalance between supply and demand, 2) significant waiting times for appointments, and 3) the limited frequency of consultation needs. These three conditions appear to be particularly relevant for our examined specialties, especially ophthalmologists and gynecologists.

On the empirical side, throughout the entire implementation period of CAS (2013 - 2016), the additional fees charged by free-billing physicians remained highly stable, as depicted in Figure B.1[33]. Furthermore, our individual price data for consultation activities confirms relative price stability over time. In fact, our primary data provider for this study, UFC Que-Choisir, also supplied price data collected in 2012, prior to the implementation of CAS. As reported in Table B.1, the slight increase in prices from 2012 to 2016 is relatively homogenous between CAS and free-billing physicians, primarily attributable to the national increase in regulated fees (2 euros for consultation). To further assess the validity of our assumption, we conducted both parametric and nonparametric statistical tests (e.g., Welch's t-test and Mann-Whitney U-test) on the evolution of the individual price gap between CAS and free-billing physicians. For consistency[34], we defined the individual price gap as the difference between the individual reference price and the weighted mean reference price of

[33]Those data are provided by the NHI (https://data.ameli.fr) and represent extra-fees for all medical acts (not only consultation)

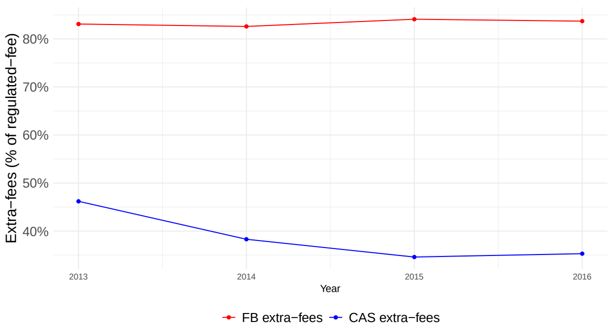
[34]In our empirical model, we defined P_i^* as the average price of physicians for consultations not made at the regulated-fee as we have detailed data on prices set by physicians. However, for 2012, we only have information on the reference price, that is, the most common price set by a physician. We thus use the reference price in 2016 to compute the evolution of the price gap.

competitors, and we measred its evolution as:

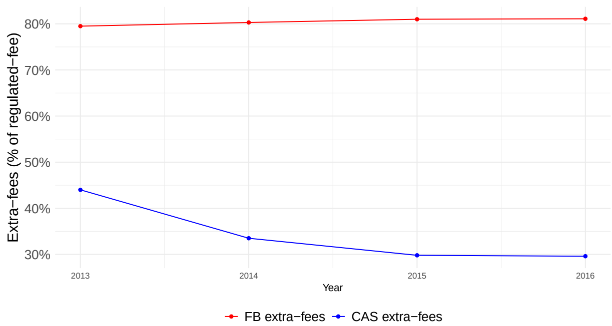
$$\Delta\text{Price gap} = (P_i^{2016} - W_i P^{2016}) - (P_i^{2012} - W_i P^{2012})$$

As shown in Table B.2, both tests across all specialties reveal no significant differences in the evolution of the price gap between CAS and free-billing physicians. All p-values (in parentheses) are significantly higher than 5%.

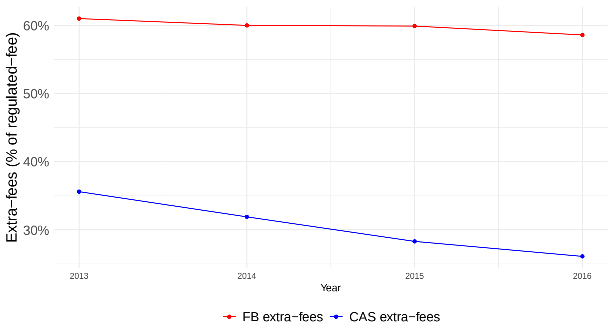
Such empirical observations are inconsistent with the alternative hypothesis that the introduction of the CAS has resulted in a new equilibrium of the local price-setting game à la Bertrand.



Gynecologists



Pediatricians



Ophtalmologists

Figure B.1: Evolution of extra-fees during the CAS implementation (2013-2016)

Specialty	CAS physicians (2016)	FB physicians (2016)	N
Ophtalmologists	0.04%	1.600%	2279
Pediatricians	1.896%	2.067%	756
Gynecologists	1.291%	1.623%	2532

Table B.1: Average annual price change between 2012 and 2016

Specialty	Welch t-test	Mann-Whitney U-test	radius (Km)
Pediatricians	0.202 (0.840)	68875 (0.121)	10
Pediatricians	0.101 (0.920)	67870 (0.230)	20
Gynecologists	-1.111 (0.267)	532876 (0.742)	10
Gynecologists	-0.843 (0.399)	533431 (0.770)	20
Ophtalmologists	0.484 (0.629)	223360 (0.7157)	10
Ophtalmologists	0.068 (0.946)	217510 (0.783)	20

Table B.2: Difference in price gap between 2012 and 2016

C The linear profit function

Consider the following Cobb-Douglas function representing the profit of a physician:

$$\Pi_i^* = \left(\frac{R_i}{R_{max}}\right)^{\alpha} \left(\frac{D_i}{D_{max}}\right)^{(1-\alpha)}$$

where R_{max} and D_{max} represent constants such that $R_i < R_{max}$ and $D_i < D_{max}$, $\forall\ i$. The logarithm of this expression can be expressed as:

$$\ln \Pi_i^* = \alpha \ln \left[1 + \frac{R_i - R_{max}}{R_{max}}\right] + (1-\alpha) \left[1 + \frac{D_i - D_{max}}{D_{max}}\right]$$

Applying the first-order Taylor approximation results in:

$$\ln \Pi_i^* = \alpha \frac{R_i}{R_{max}} + (1-\alpha) \frac{D_i}{D_{max}} - 1$$

This corresponds to a scaled version of Equation (1).

D Proof of Proposition 1

Banach fixed-point theorem: Let (P, d) be a complete normed vector space. A mapping $F : P \to P$ is a contraction mapping $\exists\, a \in [0, 1)$ such that:

$$d(F(x), F(y)) \leq ad(x, y)) \iff \frac{d(F(x), F(y))}{d(x, y))} \leq a \;\; \forall \;\; x, y \in P$$

Our proof of unicity of the equilibrium can be sketch on the following. If $F(p)$ is a contraction mapping, then there exists a unique fixed point $p^* \in [0, 1]$ such that $F(p^*) = p^*$. Since $p = F(p)$ exists only if p is an equilibrium, the fixed point p^* is the unique equilibrium of the game.

We now prove that F is a contraction mapping for the metric $d(x, y) = ||x, y||_\infty$, that is, the norm L_∞, which is given for a square matrix X, by its maximum row sum: $||X||_\infty = \max\limits_i \sum\limits_{i \neq j} x_{ij}$.

We need to show that $\frac{||(F(x)-F(y)||_\infty}{||x-y||_\infty} < 1 \,\forall\, x, y \in P$. It is well known from the mean value theorem that this is equivalent to proving that $\left|\left|\frac{\partial F(p)}{\partial p}\right|\right|_\infty < 1$.

Let $F(p) = (F_\varepsilon(q_1(p)), \ldots, F_\varepsilon(q_n(p)))'$ with $q_i(p) = \left(X_i\beta - \rho_2 W_i^{CF} p + \lambda W_i^{GF} p\right)$.

The Jacobian of $F(p)$ is:

$$\frac{\partial F(p)}{\partial p} = \lambda \begin{pmatrix} W_{11}^{GF} f_\varepsilon(q_1(p)) & \ldots & W_{1n}^{GF} f_\varepsilon(q_1(p)) \\ \vdots & \ddots & \vdots \\ W_{n1}^{GF} f_\varepsilon(q_n(p)) & \ldots & W_{nn}^{GF} f_\varepsilon(q_n(p)) \end{pmatrix} - \rho_2 \begin{pmatrix} W_{11}^{CF} f_\varepsilon(q_1(p)) & \ldots & W_{1n}^{CF} f_\varepsilon(q_1(p)) \\ \vdots & \ddots & \vdots \\ W_{n1}^{CF} f_\varepsilon(q_n(p)) & \ldots & W_{nn}^{CF} f_\varepsilon(q_n(p)) \end{pmatrix} \tag{A.1}$$

where $f_\varepsilon(.)$ is the probability density function derived from the cumulative distribution function $F_\varepsilon(.)$ such that $F'_\varepsilon(.) = f_\varepsilon(.)$. Expressing the L_∞ norm of Equation A.1 yields the following:

$$\begin{aligned}
\left|\left|\frac{\partial F(p)}{\partial p}\right|\right|_\infty &= \max_{i \in \mathcal{N}} \left\{ \left| \lambda \begin{pmatrix} W_{11}^{GF} f_\varepsilon(q_1(p)) & \ldots & W_{1n}^{GF} f_\varepsilon(q_1(p)) \\ \vdots & \ddots & \vdots \\ W_{n1}^{GF} f_\varepsilon(q_n(p)) & \ldots & W_{nn}^{GF} f_\varepsilon(q_n(p)) \end{pmatrix} - \rho_2 \begin{pmatrix} W_{11}^{CF} f_\varepsilon(q_1(p)) & \ldots & W_{1n}^{CF} f_\varepsilon(q_1(p)) \\ \vdots & \ddots & \vdots \\ W_{n1}^{CF} f_\varepsilon(q_n(p)) & \ldots & W_{nn}^{CF} f_\varepsilon(q_n(p)) \end{pmatrix} \right| \right\} \\
&= \left| \lambda \max_{i \in \mathcal{N}} \sum_{j \neq i}^{n} \left[W_{ij}^{GF} f_\varepsilon(q_i(p))\right] - \rho_2 \max_{i \in \mathcal{N}} \sum_{j \neq i}^{n} \left[W_{ij}^{CF} f_\varepsilon(q_i(p))\right] \right| \\
&\leq \left| \lambda \left|\left|W^{GF}\right|\right|_\infty \max_q f_\varepsilon(q) - \rho_2 \left|\left|W^{CF}\right|\right|_\infty \max_q f_\varepsilon(q) \right| \\
&\leq \left|\lambda - \left|\left|W^{CF}\right|\right|_\infty \rho_2\right| \left|\max_q f_\varepsilon(q)\right|
\end{aligned} \tag{A.2}$$

where the first inequality follows by the definition of the L_∞ norm, i.e. $\left|\left|W^{CF}\right|\right|_\infty = \max\limits_{i \in \mathcal{N}} \sum\limits_{j \neq i}^{n} w_{ij}^*$ and $\left|\left|W^{GF}\right|\right|_\infty = \max\limits_{i \in \mathcal{N}} \sum\limits_{j \neq i}^{n} w_{ij}^{**}$. The second inequality is derived from Assumption 3 ($\left|\left|W^{GF}\right|\right|_\infty = 1$) and the multiplicativity of the absolute values. Note also that $0 \leq \max\limits_q f_\varepsilon(q)$ by definition is such that $|\max\limits_q f_\varepsilon(q)| = \max\limits_q f_\varepsilon(q)$.

Thus, F is a contraction mapping if:

$$
\begin{aligned}
&\left|\left|\frac{\partial F(p)}{\partial p}\right|\right|_{\infty} \leq \left|\lambda - \left|\left|W^{CF}\right|\right|_{\infty} \rho_2\right| \max_{q} f_{\varepsilon}(q) < 1 \\
&\leftrightarrow \left|\lambda - \left|\left|W^{CF}\right|\right|_{\infty} \rho_2\right| < \frac{1}{\max_{q} f_{\varepsilon}(q)}
\end{aligned}
\tag{A.3}
$$

It is important to note that this restriction on the strengths of peer effects is 1) related to and 2) more restrictive than the condition in Lee et al. (2014)'s model. In their framework, the condition for the uniqueness of the equilibrium is simply $|\lambda| < \frac{1}{\max_{q} f_{\varepsilon}(q)}$, as they exclusively consider one type of interaction: conformity to social norms.

E Variance-covariance matrix of the NPL estimator

Proposition 2 shows that the asymptotic variance of the NPL estimator can be estimated as $\Omega_1(\hat{\kappa}_{NPL})^{-1}\Omega_2(\hat{\kappa}_{NPL})\Omega_1(\hat{\kappa}_{NPL})^{-1}$, where

$$-\mathbb{E}\left[\frac{\partial^2\tilde{\mathcal{L}}(\hat{\kappa}_{NPL},p^*)}{\partial\kappa\partial\kappa'}\right] \xrightarrow{p} \Omega_2(\kappa_0)$$

$$\mathbb{E}\left[\frac{\partial^2\tilde{\mathcal{L}}(\hat{\kappa}_{NPL},p^*)}{\partial\kappa\partial\kappa'} + \frac{\partial^2\tilde{\mathcal{L}}(\hat{\kappa}_{NPL},p^*)}{\partial\kappa\partial p'} \cdot \left[I - \left(\frac{\partial\Gamma(\hat{\kappa}_{NPL},p^*)}{\partial p}\right)\right]^{-1} \cdot \frac{\partial\Gamma(\hat{\kappa}_{NPL},p^*)}{\partial\kappa'}\right] \xrightarrow{p} \Omega_1(\hat{\kappa}_{NPL})$$

Let $K^* = \left[X \;\; W^{CF}(\mathbf{1_n} - p^*) \;\; W^{GF}\left(p^* - \frac{1}{2}\mathbf{1_n}\right)\right]$ be the $n \times dim(K^*)$ matrix of variables in the model. Due to the logit form in $p^* = \Gamma(\hat{\kappa}_{NPL}, p^*)$, the gradient is given by:

$$\frac{\partial\tilde{\mathcal{L}}(\hat{\kappa}_{NPL},p^*)}{\partial\kappa} = \frac{1}{n}K\big(y - \Gamma(\hat{\kappa}_{NPL},p^*)\big),$$

the Hessian matrix is equal to:

$$\frac{\partial^2\tilde{\mathcal{L}}(\hat{\kappa}_{NPL},p^*)}{\partial\kappa\partial\kappa'} = -\frac{1}{n}K'Kp^*(1-p^*),$$

while

$$\frac{\partial^2\tilde{\mathcal{L}}(\hat{\kappa}_{NPL},p^*)}{\partial\kappa\partial p} = -\frac{1}{n}K'p^*(1-p^*)\big(\hat{\lambda}W^{GF} - \hat{\rho}_2W^{CF}\big),$$

and

$$\frac{\partial\Gamma(\hat{\kappa}_{NPL},p^*)}{\partial p} = p^*(1-p^*)\big(\hat{\lambda}W^{GF} - \hat{\rho}_2W^{CF}\big),$$

and finally

$$\frac{\partial\Gamma(\hat{\kappa}_{NPL},p^*)}{\partial\kappa} = Kp^*(1-p^*).$$

F Computation of the marginal effects

The marginal effects of the expected share of the competitors and peers selecting $y_j = 1$ ($W_i^{CF}p^*$ and $W_i^{GF}p^*$, respectively) on the probability that the player i selects $y_i = 1$ can be derived as follows:

$$\frac{\partial p_i^*}{\partial W_i^{CF}p^*} = -p_i^*(1-p_i^*)\hat{\rho_2}$$

$$\frac{\partial p_i^*}{\partial W_i^{GF}p^*} = p_i^*(1-p_i^*)\hat{\lambda}$$

Here, $\hat{\rho_2}$ and $\hat{\lambda}$ represent the estimated parameters obtained from the final stage of the iterative maximization of the log-likelihood function as described in Equation (8). These marginal effects are consistent with the standard form observed in logit models, since $W_i^{CF}p^*$ and $W_i^{GF}p^*$ are directly incorporated into the log-likelihood function.

However, the marginal effects of individual variables differ from those in standard logit models because these variables not only affect the individual's probability of choosing $y_i = 1$ through the *own effects* β, but also influence the formation of rational expectations regarding peers' strategies, thus altering the rational expectations equilibrium p^*, which we denote as *RE effects*. In fact, players connected to i will update their rational expectations of i's strategy if her characteristics change. If ρ_2 and λ are significant, players connected to i will subsequently adjust their strategies following the update of their rational expectations about i's strategy. These adjustments then feedback into the best response strategy of i through competitive interaction and conformity.

The total marginal effect of an increase of X_{ik}, on the strategy of i is then given by:

$$\begin{aligned}\underbrace{\frac{dp_i^*}{dX_{ik}}}_{\text{total effect}} &= \underbrace{\frac{\partial p_i^*}{\partial X_{ik}}}_{\text{own effect}} + \underbrace{\frac{\partial p_i^*}{\partial p^*}\frac{\partial p^*}{\partial X_{ik}}}_{\text{RE effect}} = \frac{\partial p_i^*}{\partial X_{ik}} + \frac{\partial p_i^*}{\partial (W_i^{CF}p^*)}\frac{\partial (W_i^{CF}p^*)}{\partial X_{ik}} + \frac{\partial p_i^*}{\partial (W_i^{GF}p^*)}\frac{\partial (W_i^{GF}p^*)}{\partial X_{ik}} \\ &= \hat{\beta}_k p_i^*(1-p_i^*) + \left(\hat{\lambda}p_i^*(1-p_i^*)W_i^{GF} - \hat{\rho_2}p_i^*(1-p_i^*)W_i^{CF}\right) \times \left\{\left[\hat{\lambda}\sum_{j\neq i} w_{ji}^{**}\hat{\beta}_k - \hat{\rho_2}\sum_{j\neq i} w_{ji}^{*}\hat{\beta}_k\right]p^*(1-p^*)\right\} \\ &= p_i^*(1-p_i^*)\left(\hat{\beta}_k + \left(\hat{\lambda}W_i^{GF} - \hat{\rho_2}W_i^{CF}\right) \times \left\{\left[\hat{\lambda}\sum_{j\neq i} w_{ji}^{**}\hat{\beta}_k - \hat{\rho_2}\sum_{j\neq i} w_{ji}^{*}\hat{\beta}_k\right]p^*(1-p^*)\right\}\right)\end{aligned} \tag{12}$$

G Proof of Proposition 3

Our structural model is given by $p^* = F_\varepsilon\left(p^*, X, W^{CF}, W^{GF}; \kappa\right)$. Let κ and $\widetilde{\kappa}$ be two sets of parameters. We then have:

$$p^* = F_\varepsilon\left(p^*, X, W^{CF}, W^{GF}; \kappa\right)$$
$$\widetilde{p}^* = F_\varepsilon\left(\widetilde{p}^*, X, W^{CF}, W^{GF}; \widetilde{\kappa}\right)$$

Our model is identified if κ and $\widetilde{\kappa}$ are observationally equivalent, i.e. if $p^* = \widetilde{p}^*$, which implies that $F_\varepsilon\left(p^*, X, W^{CF}, W^{GF}; \kappa\right) = F_\varepsilon\left(\widetilde{p}^*, X, W^{CF}, W^{GF}; \widetilde{\kappa}\right)$. Under Assumption 6 (ii), F_ϵ is continuous and the condition for observational equivalence yields:

$$F_\varepsilon\left(p^*, X, W^{CF}, W^{GF}; \kappa\right) - F_\varepsilon\left(\widetilde{p}^*, X, W^{CF}, W^{GF}; \widetilde{\kappa}\right) = 0$$

Using Equation (11), the above equality can be rewritten as:

$$\begin{aligned}
0 =& (\alpha - \widetilde{\alpha})(\theta - \widetilde{\theta})\left(\delta \overline{P}_1\right) - (\alpha - \widetilde{\alpha})\left((1-\delta)dP\right) + (1 - \alpha - (1 - \widetilde{\alpha}))[Z\left((\Phi - \widetilde{\Phi})(\gamma(1) - 1 - (\widetilde{\gamma}(1) - 1))\right) - \\
& (\eta_1 - \widetilde{\eta}_1)(\gamma(1) - \widetilde{\gamma}(1))W^{CFR}\mathbf{1_m} + (\eta_2 - \widetilde{\eta}_2)\left(\gamma(1) - 1 - (\widetilde{\gamma}(1) - 1)\right)W^{CF}(\mathbf{1_n} - p) + (\eta_2 - \widetilde{\eta}_2)W^{CF}\mathbf{1_n}] \\
& + (\lambda - \widetilde{\lambda})W^{GF}\left(p - \frac{1}{2}\mathbf{1_n}\right) \\
& = \left[\delta \overline{P}_1 \quad -(1-\delta)dP \quad Z \quad W^{CFR}\mathbf{1_m} \quad W^{CF}(\mathbf{1_n} - p) \quad W^{CF}\mathbf{1_n} \quad W^{GF}\left(p - \frac{1}{2}\mathbf{1_n}\right)\right] \times \\
& \Big((\alpha - \widetilde{\alpha})(\theta - \widetilde{\theta}), \alpha - \widetilde{\alpha}, (\widetilde{\alpha} - \alpha)(\Phi - \widetilde{\Phi})(\gamma(1) - \widetilde{\gamma}(1)), (\widetilde{\alpha} - \alpha)(\eta_1 - \widetilde{\eta}_1)(\gamma(1) - \widetilde{\gamma}(1)), (\widetilde{\alpha} - \alpha)(\eta_2 - \widetilde{\eta}_2)(\gamma(1) - \widetilde{\gamma}(1)), \\
& (\widetilde{\alpha} - \alpha)(\eta_2 - \widetilde{\eta}_2), \lambda - \widetilde{\lambda}\Big)' \\
& = K\Big((\alpha - \widetilde{\alpha})(\theta - \widetilde{\theta}), \alpha - \widetilde{\alpha}, (\widetilde{\alpha} - \alpha)(\Phi - \widetilde{\Phi})(\gamma(1) - \widetilde{\gamma}(1)), (\widetilde{\alpha} - \alpha)(\eta_1 - \widetilde{\eta}_1)(\gamma(1) - \widetilde{\gamma}(1)), (\widetilde{\alpha} - \alpha)(\eta_2 - \widetilde{\eta}_2)(\gamma(1) - \widetilde{\gamma}(1)), \\
& (\widetilde{\alpha} - \alpha)(\eta_2 - \widetilde{\eta}_2), \lambda - \widetilde{\lambda}\Big)'
\end{aligned} \tag{A.6}$$

Recall that Assumption 6 (i) implies that none of the columns of K are zero columns and that no columns of K are linearly dependent. Thus, Equation (A.6) holds only if:

(i) $(\alpha - \widetilde{\alpha})(\theta - \widetilde{\theta})$

(ii) $\alpha - \widetilde{\alpha} = 0$

(iii) $(\widetilde{\alpha} - \alpha)(\Phi - \widetilde{\Phi})(\gamma(1) - \widetilde{\gamma}(1)) = 0$

(iv) $(\widetilde{\alpha} - \alpha)(\eta_1 - \widetilde{\eta}_1)(\gamma(1) - \widetilde{\gamma}(1))$

(v) $(\widetilde{\alpha} - \alpha)(\eta_2 - \widetilde{\eta}_2)(\gamma(1) - \widetilde{\gamma}(1)) = 0$

(vi) $(\widetilde{\alpha} - \alpha)(\eta_2 - \widetilde{\eta}_2) = 0$

(vii) $\lambda - \widetilde{\lambda} = 0$

Condition (ii) implies that Equation (A.6) holds only if $\alpha = \widetilde{\alpha}$. Then, condition (i) is satisfied only if $\theta = \widetilde{\theta}$. Similarly, condition (vii) holds only if $\lambda = \widetilde{\lambda}$ Note that condition (iii) can be rewritten as:

$$
\begin{aligned}
0 &= \widetilde{\alpha}\Phi\gamma(1) - \widetilde{\alpha}\widetilde{\Phi}\gamma(1) - \alpha\Phi\gamma(1) + \alpha\widetilde{\Phi}\gamma(1) - \widetilde{\alpha}\Phi\widetilde{\gamma}(1) + \widetilde{\alpha}\widetilde{\Phi}\widetilde{\gamma}(1) + \alpha\Phi\widetilde{\gamma}(1) - \alpha\widetilde{\Phi}\widetilde{\gamma}(1) \qquad \text{(A.7)} \\
&= (\widetilde{\alpha}\Phi\gamma(1) - \widetilde{\alpha}\widetilde{\Phi}\gamma(1)) + (\alpha\Phi\widetilde{\gamma}(1) - \alpha\Phi\gamma(1)) + (\widetilde{\alpha}\widetilde{\Phi}\widetilde{\gamma}(1) - \alpha\widetilde{\Phi}\widetilde{\gamma}(1)) + (\alpha\widetilde{\Phi}\gamma(1) - \widetilde{\alpha}\Phi\widetilde{\gamma}(1))
\end{aligned}
$$

Equation (A.7) is valid only if each term within the brackets is equal to zero. Under Assumption 6(iii), $\alpha, \phi, \gamma(1) \neq 0$ and it is straightforward to show that:

A. $(\alpha\Phi\widetilde{\gamma}(1) - \alpha\Phi\gamma(1)) = 0 \iff \widetilde{\gamma}(1) = \gamma(1)$

B. $(\widetilde{\alpha}\widetilde{\Phi}\widetilde{\gamma}(1) - \widetilde{\alpha}\Phi\widetilde{\gamma}(1)) = 0 \iff \widetilde{\Phi} = \Phi$

C. $(\widetilde{\alpha}\widetilde{\Phi}\widetilde{\gamma}(1) - \alpha\widetilde{\Phi}\widetilde{\gamma}(1)) = 0 \iff \widetilde{\alpha} = \alpha$

D. $(\alpha\widetilde{\Phi}\gamma(1) - \widetilde{\alpha}\Phi\widetilde{\gamma}(1)) = 0 \Leftarrow \widetilde{\gamma}(1) = \gamma(1) \wedge \widetilde{\Phi} = \Phi \wedge \widetilde{\alpha} = \alpha$

Note that $A \wedge B \wedge C \implies D$, such that condition (iii) holds only if $\gamma(1) = \widetilde{\gamma}(1), \Phi = \widetilde{\Phi}$ and $\alpha = \widetilde{\alpha}$. We can use the same derivation to show that under Assumption 6(iii) condition (iv) holds only if $\gamma(1) = \widetilde{\gamma}(1)$, $\alpha = \widetilde{\alpha}$ and $\eta_1 = \widetilde{\eta}_1$. Condition (v) holds only if $\gamma(1) = \widetilde{\gamma}(1)$, $\alpha = \widetilde{\alpha}$ and $\eta_2 = \widetilde{\eta}_2$. Similarly, condition (vi) is satisfied only if $\alpha = \widetilde{\alpha}$ and $\eta_2 = \widetilde{\eta}_2$.

Then, Equation (A.6) is valid only if $\alpha = \widetilde{\alpha}$, $\theta = \widetilde{\theta}$, $\Phi = \widetilde{\Phi}$, $\gamma(1) = \widetilde{\gamma}(1)$, $\eta_1 = \widetilde{\eta}_1$, $\eta_2 = \widetilde{\eta}_2$ and $\lambda = \widetilde{\lambda}$. Hence, the observational equivalence of κ and $\widetilde{\kappa}$ implies that $\kappa = \widetilde{\kappa}$, our structural model, is identified. ■

H Justification of the empirical weighted distance functions

One of the main criticisms of spatial econometrics is the challenge of defining the spatial weight matrix. Specifically, it is often difficult to justify both the selection of nodes and the assignment of weights from a theoretical perspective. In this paper, we address this issue by employing a purely data-generating process (DGP)-based approach to define the nodes and weights. This appendix provides the rationale for our choice of distance-based weighting functions. For all specialties, we generate spatial correlograms graphs for CAS choices and reference prices. The results consistently reveal a clear negative exponential relationship with respect to distance. Although this relationship appears relatively homogeneous among specialties for the price variable, it exhibits notable heterogeneity for the CAS choice. Specifically, Figures H.1 to H.3 highlight significantly higher convexity for ophthalmologists compared to the other two specialties. Furthermore, the degree of convexity is considerably greater for the CAS variable than for the price variable, irrespective of the specialty. It is important to interpret these findings with caution, as analyzing correlations involving a binary outcome, like the CAS choice, is inherently different from analyzing continuous variables, such as prices. The correlations for binary outcomes tend to be weaker (stronger) depending on whether the sample mean is lower (higher) than 0.5. However, the substantial differences observed in convexity suggest that different convexity parameters should be applied when constructing the weight matrix for free-billing CAS choices (W^{CF}) and the weight matrix for free-billing prices (W^P) within each specialty. A final point concerns the spatial weights linking free-billing and regulated-fee physicians, which capture the potential for patient poaching by free-billing physicians when they adopt the CAS. In other words, this final point involves modeling the weights in W^{CFR}. However, it is challenging to directly assess this relationship, as regulated-fee physicians do not have the option to adopt CAS. Out of curiosity, we performed a spatial correlation analysis using the full sample of physicians, assuming that all regulated-fee physicians adopted the CAS (available upon request). We obtain similar convex relationships across specialties compared to those presented earlier, but with significantly higher convexity, approximately twice as high. Although this result should be interpreted with caution given the strong assumption underlying the analysis, it suggests that a more convex weighting function should be considered for W^{CFR} compared to W^{CF}.

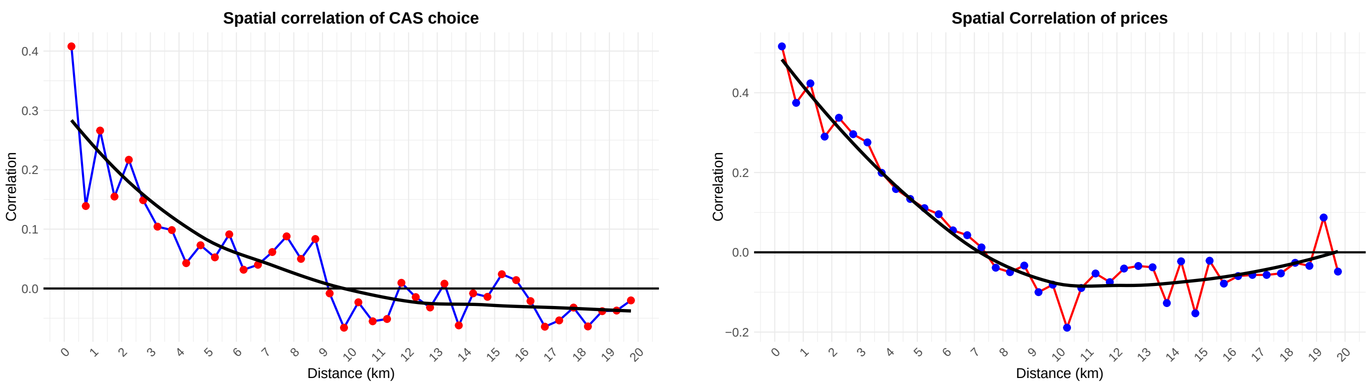


Figure H.1: Spatial correlograms for pediatricians in sector 2

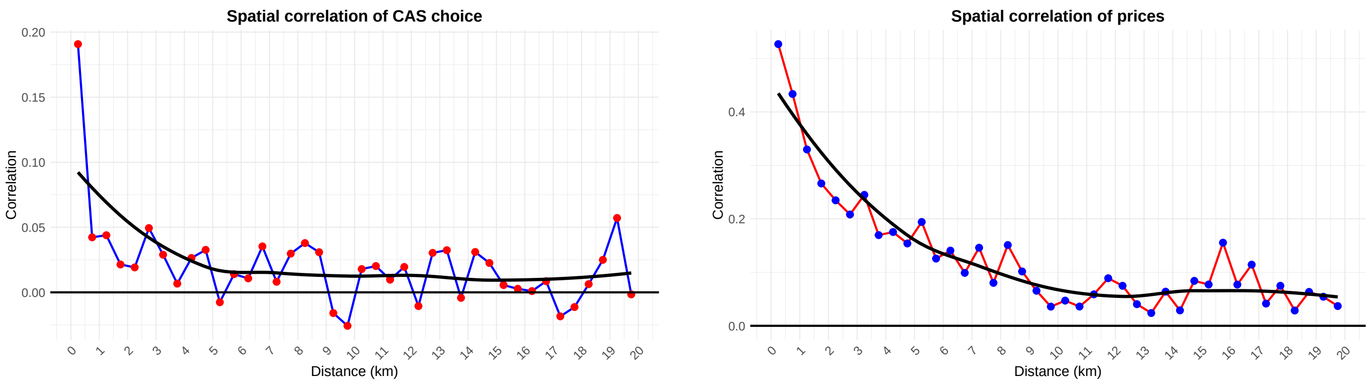


Figure H.2: Spatial correlograms for ophtalmologists in sector 2

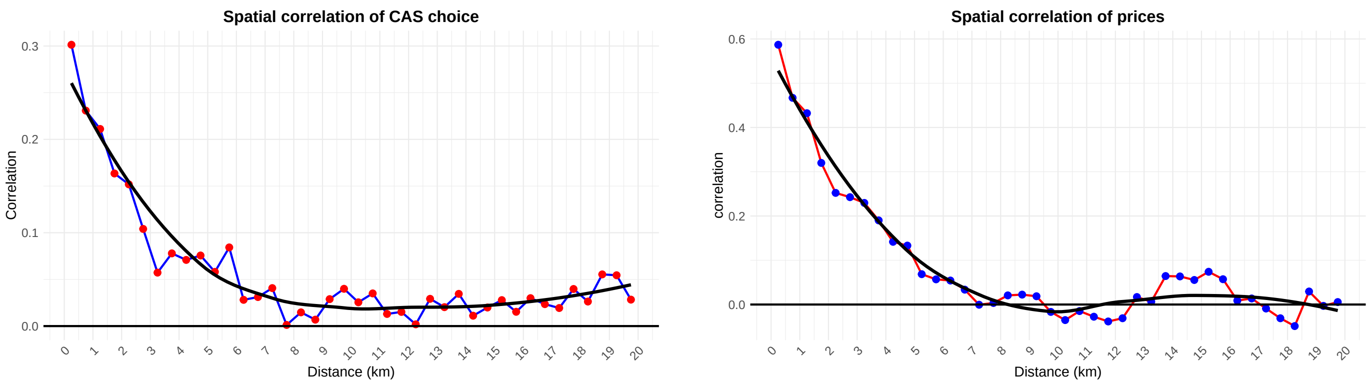


Figure H.3: Spatial correlograms for gynecologists in sector 2

To determine the convexity parameters for the spatial weights (W^{CF}, W^{CFR}, W^{P}), we first focus on the price variable, which is continuous and therefore more straightforward to analyze. Based on this, we adopt the following cautious rule for parameter selection: param(W^{P}) $<$ param(W^{CF}) $<$ param(W^{CFR}). From Figures H.1 to H.3, identifying reasonable convexity parameters for the price variable is relatively straightforward. For the other two weights, we primarily account for the observed heterogeneity across specialties. Given that CAS is a binary variable and spatial correlations involving binary outcomes necessitate careful interpretation, the parameters for W^{CF} and W^{CFR} are selected with particular caution, as previously discussed.

Specialty	W^{CF}	W^{CFR}	WP
Pediatricians	-0.5	-0.7	-0.4
Gynecologists	-0.5	-0.7	-0.35
Ophtalmologists	-0.6	-0.8	-0.4

Table H.1: Convex parameters retained for the different weight matrix

I Computation of $\hat{\delta}_i$ and $\hat{P}_i^*$

To calculate the estimated share of consultations performed at the regulated fee ($\hat{\delta}_i$), we utilize the available data on physicians' consultation prices. In France, free-billing physicians are allowed to engage in price discrimination. Although we observe the reference price (the most common price set for a consultation denoted P_r) for each physician, we also have for approximately 60% of them[35] information on the share of consultation made at this reference price (s_r) as well as their minimum (P_{min}) and maximum (P_{max}) prices. We consider $P_r = P_{min} = P_{max}$ when information on s_r is not available. This assumption is reasonable, given that price discrimination is not practiced by all physicians. Using these inputs, we calculate the estimated value of δ_i through the following rules:

$$\hat{\delta}_i = \begin{cases} = 0 & \text{if } P_{min} > \overline{P}_R \\ = (1 - s_r)/2 & \text{if } P_{min} \leq \overline{P}_R \ \& \ P_r < P_{max} \ \& \ P_r > P_{min} \\ = 1 - s_r & \text{if } P_{min} \leq \overline{P}_R \ \& \ P_r = P_{max} \ \& \ P_r > P_{min} \\ = s_r & \text{if } P_r \leq \overline{P}_R \ \& \ P_{max} > \overline{P}_F \\ = 1 & \text{if } P_r \leq \overline{P}_R \ \& \ P_{max} \leq \overline{P}_R \end{cases}$$

where $P_R = 28$ is the regulated-fee for a consultation.

This estimate of δ_i is subject to measurement error, which may introduce bias into the analysis. To assess the potential for smearing effects, we calculate an alternative estimate of δ_i using the following approach: $\hat{\delta}_i(a) = \hat{\delta}_i + \mathcal{U}(0, \overline{\delta}(a))$, where $\overline{\delta}(a)$ is the NUTS3 empirical mean of $\hat{\delta}_i$. In this context, $\mathcal{U}$ represents the uniform distribution. For further details, please refer to the robustness section of the paper.

Using the diverse prices available in the dataset, we can compute an estimated value for P_i^*, which represents the average free-billing price of a consultation. In our theoretical framework, P_i^* denotes the free-billing price set by physician i. We implicitly assume there is no price discrimination; however, this assumption is not reflective of reality, as previously discussed. Our computed measure more accurately represents physician pricing practices compared to the reference price (P_r), enabling us to better account for the financial (dis)incentives provided by the CAS. Specifically, we calculated the empirical value of P_i^* using the following rules:

$$\hat{P}_i^* = \begin{cases} = s_r \times P_r + (1 - s_r) \times P_{min} & \text{if } P_{min} > \overline{P}_R \ \& \ P_r = P_{max} \\ = s_r \times P_r + (1 - s_r) \times P_{max} & \text{if } P_{min} > \overline{P}_R \ \& \ P_r = P_{min} \\ = s_r \times P_r + \frac{(1-s_r)}{2} \times P_{min} + \frac{(1-s_r)}{2} \times P_{max} & \text{if } P_{min} > \overline{P}_R \ \& \ P_{min} < P_r \ \& \ P_{max} > P_r \\ = \frac{2}{1+s_r} \left[s_r \times P_r + \frac{(1-s_r)}{2} \times P_{max} \right] & \text{if } P_{min} < \overline{P}_R \ \& \ P_r > P_{min} \ \& \ P_r < P_{max} \\ = P_r & \text{if } P_{min} < \overline{P}_R \ \& \ P_{max} = P_r \\ = P_r & \text{otherwise} \end{cases}$$

[35] 57% for pediatricians, 54% for ophthalmologists and 65% for gynecologists.

J Descriptive statistics for covariates

Table J.1 presents descriptive statistics for the main variables used in the empirical analysis, disaggregated by specialty.

Variable	Mean	S.D.	Min	p25	p75	Max
			Pediatricians			
Average FB price	49.903	13.996	25	41	55	160
$\hat{\delta}_i$	0.120	0.251	0	0	.100	1
Price gap	−0.699	11.251	−46.095	−6.663	4.278	90.052
Pop	0.177	0.097	0.095	0.135	0.190	0.894
Income	2.275	0.231	1.722	2.100	2.461	3.050
CMUC	0.086	0.026	0.029	0.071	0.095	0.176
Gender	0.575	0.495	0	0	1	1
New	0.242	0.429	0	0	0	1
Multi	1.136	0.410	1	1	1	7
			Ophthalmologists			
Average FB price	51.125	15.619	25	42	56	200
$\hat{\delta}_i$	0.107	0.237	0	0	0	1
Price gap	−0.544	11.763	−49.342	−5.604	4.162	108.595
Pop	0.125	0.076	0.044	0.090	0.137	1.608
Income	2.207	0.223	1.718	2.046	2.411	3.145
CMUC	0.087	0.027	0.024	0.072	0.097	0.176
Gender	0.352	0.478	0	0	1	1
New	0.144	0.351	0	0	0	1
Multi	1.502	0.925	1	1	2	8
			Gynecologists			
Average FB price	57.233	16.287	25	47.5	64.100	180
$\hat{\delta}_i$	0.118	0.238	0	0	0.100	1
Price gap	−0.685	12.527	−59.202	−6.841	.142	72.611
Pop	0.103	0.060	0.052	0.075	0.113	1.052
Income	2.237	0.224	1.721	2.075	2.445	3.147
CMUC	0.087	0.026	0.024	0.073	0.097	0.176
Gender	0.486	0.500	0	0	1	1
New	0.173	0.378	0	0	0	1
Multi	1.266	0.604	1	1	1	7

Table J.1: Descriptive statistics of variables.

The average free-billing price for consultations is relatively similar between pediatricians and ophthalmologists (approximately 50 euros), while it is significantly higher for gynecologists at 57.2 euros. Regarding the proportion of activity performed at regulated fees, our estimated values of $\hat{\delta}_i$ indicate relatively similar averages and distributions across specialties. We estimate that, on average, free-billing pediatricians perform 12% of their activities at regulated fees, compared to 10.7% for ophthalmologists and 11.8% for gynecologists. In terms of the price gap (defined as the difference between the individual price and the competitor reference price), we observe substantial variance, with 50% of the most central observations falling within the interval [-5.6 ; 4.2]. The patient base, as measured by the Pop variable, indicates an average of 17,700 inhabitants per pediatrician, 12,500 per ophthalmologist, and 10,300 per gynecologist. The average income, along with the proportion of low-income patients within a 20 km radius of healthcare providers, is relatively similar across specialties, approximately €22,000 and 9%, respectively.

In terms of personal and practice characteristics, pediatricians is the most feminized profession in our sample, with 57.5% of practitioners being women, compared to 48.6% in gynecology and only 35.2% in ophthalmology. In addition, new physicians (those practicing for less than four years) make up approximately 24% pediatricians, 14% ophthalmologists, and 17% gynecologists.

As explained in Section 5.2, the French healthcare system classifies free-billing physicians into four distinct categories. As shown in Table J.2, over one-third of the free-billing physicians in our database operate under a status other than purely liberal.

Status	**Pediatricians**	**Ophthalmologists**	**Gynecologists**
Liberal (Type 0)	56.04%	66.72%	59.91%
Hospital practitioner (Type 1)	2.82%	6.09%	12.21%
Liberal & Hospital (Type 2)	25.65%	17.05%	16.85%
Liberal & Employed (Type 3)	15.49%	10.14%	11.03%
Count	994	2660	3055

Table J.2: Free-billing physicians' status

As introduced in Section 5.2, some free-billing physicians operate in multiple locations. While their status captures part of this information, it does not fully account for it. For example, physicians with a "Liberal" status can practice in different locations, whereas those with a "Liberal & Hospital" status may spend minimal time in the hospital and are not classified by the NHI as practicing in multiple locations[36]. The original NHI database provides information on all locations where a physician meets this activity threshold, allowing us to count the number of locations in which they operate ($Multi$). As shown in Table J.1, ophthalmology has the highest share of multi-location practitioners, with an average of 1.5 locations per physician. This is notably higher than for gynecologists and even more so for pediatricians. A small number of physicians operate in a large number of locations, with a maximum of 7 for pediatricians and gynecologists and 8 for ophthalmologists.

[36]The NHI dataset used in this paper imposes a minimum activity threshold to classify a physician as working in a particular location.

K Selection of radius

In this appendix, we present the log-likelihood and the estimates of five key parameters for the reduced-form model (7) under various radius values, which define the competitive area for each physician. It is important to note that for any sample and any selected radius (ranging from 1 to 20 km), the centrality ($W_i^{CF}\mathbf{1_n}$) and competition effects ($W_i^{CF}(\mathbf{1_n} - p)$), ($W_i^{CFR}\mathbf{1_n}$) are insignificant, while the conformity effect ($W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$) and price gap are significant.

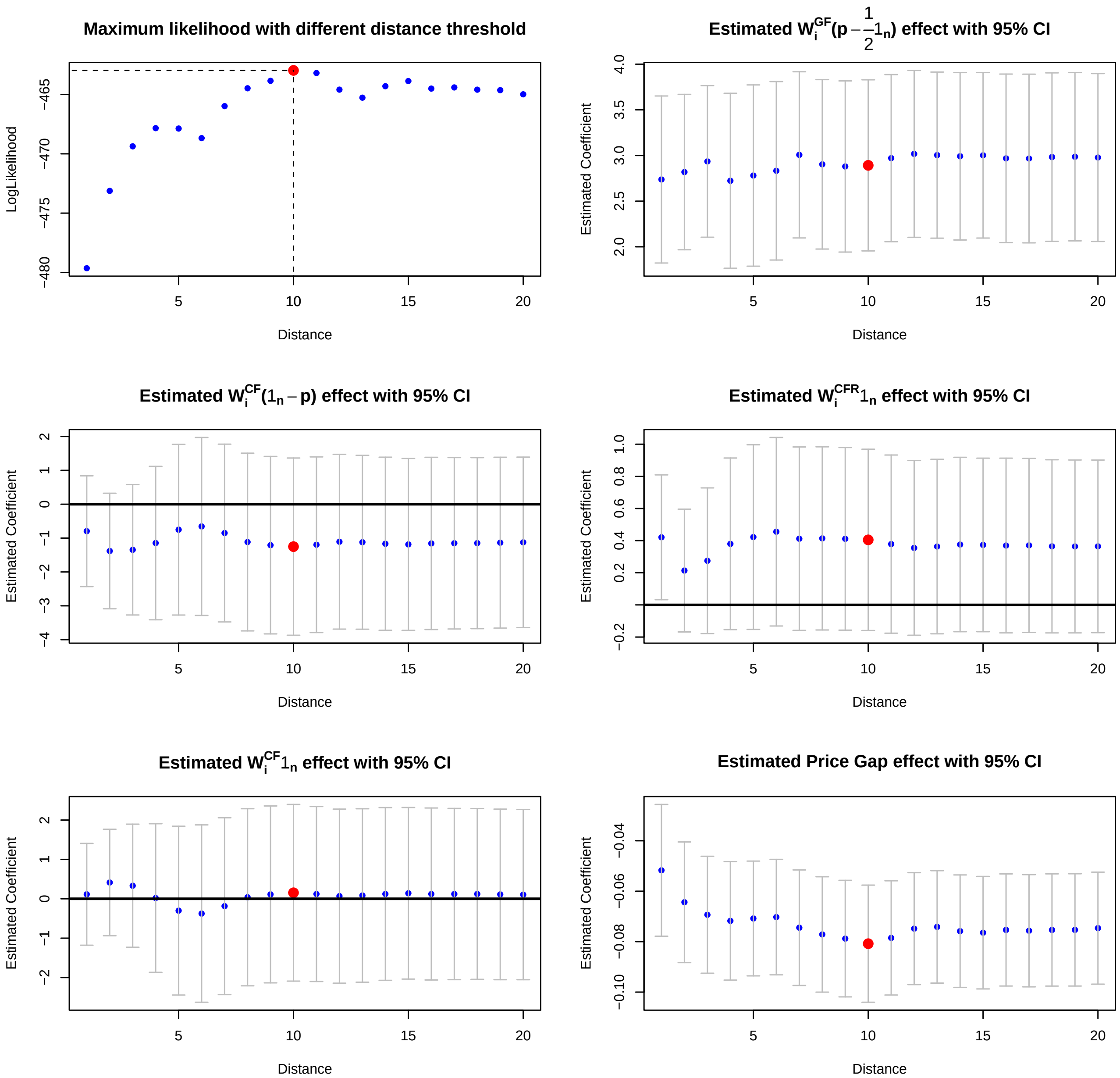


Figure K.1: Selection of radius for pediatricians

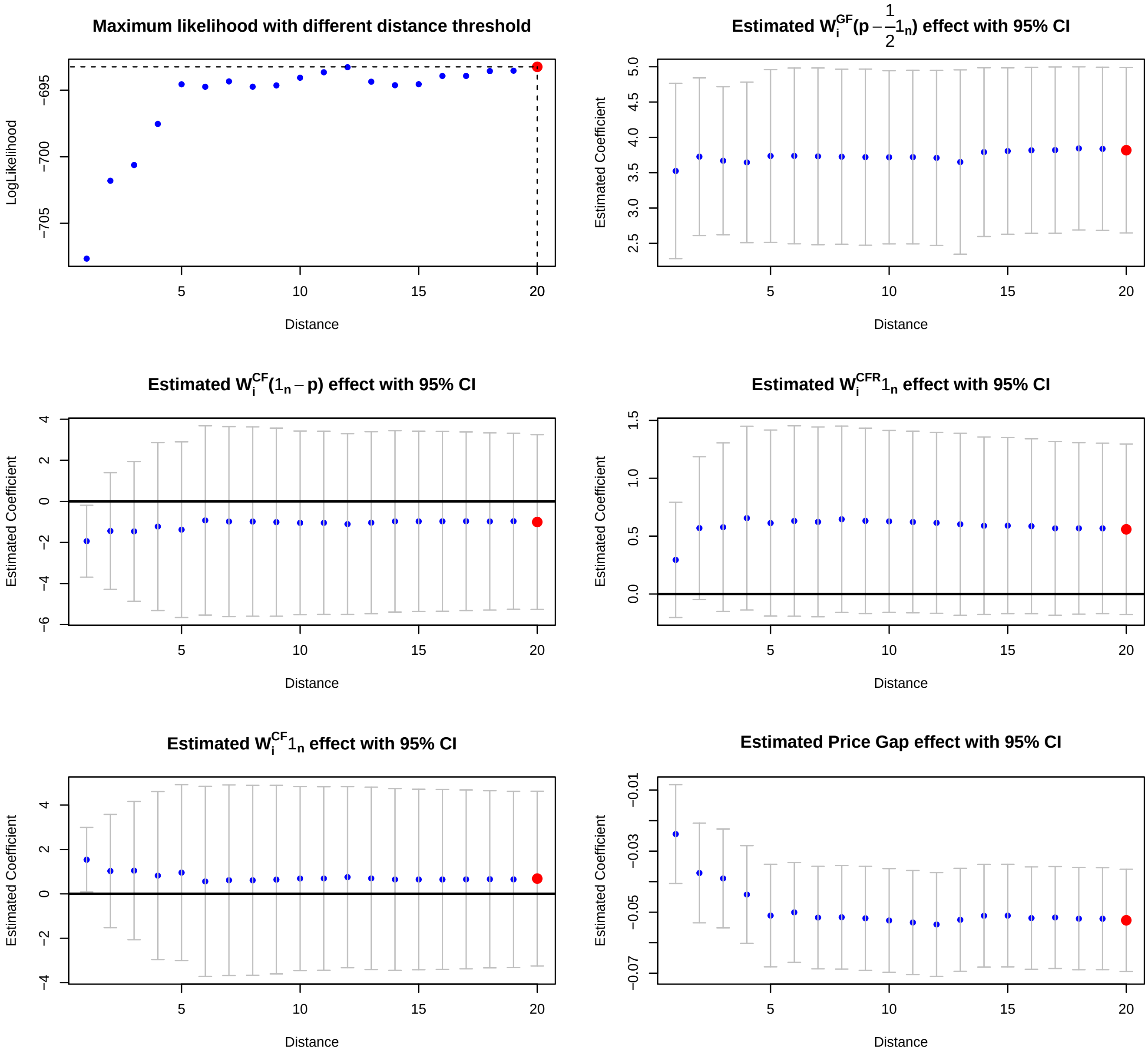


Figure K.2: Selection of radius for ophthalmologists

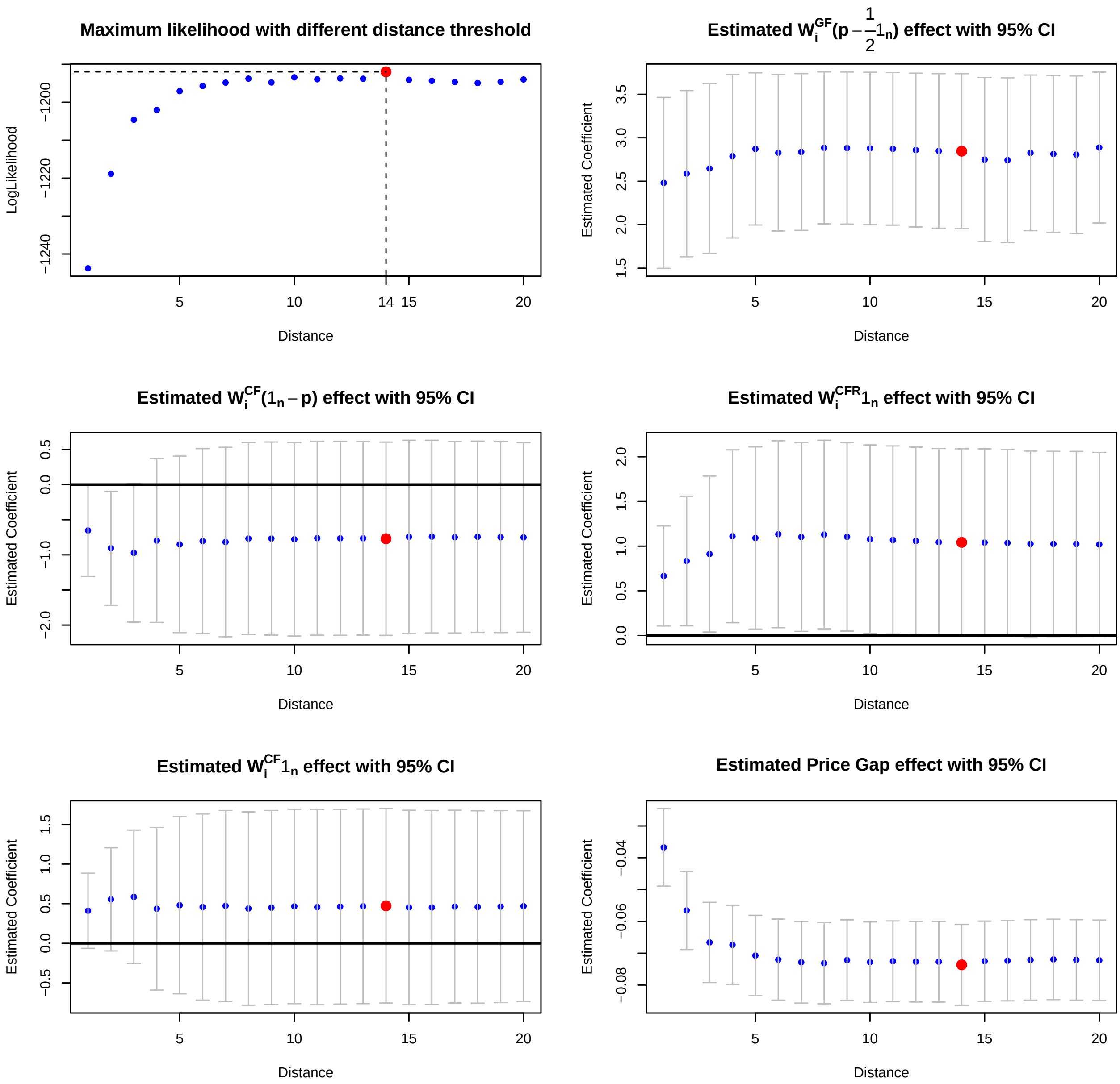


Figure K.3: Selection of radius for gynecologists

In what follows, we compare the spatial concentration of our three medical specialties with that of schools. We measure the spatial concentration of our data points using the K_d function proposed by Duranton & Overman (2005). For a comprehensive review of distance-based spatial concentration measures, refer to Marcon & Puech (2017).

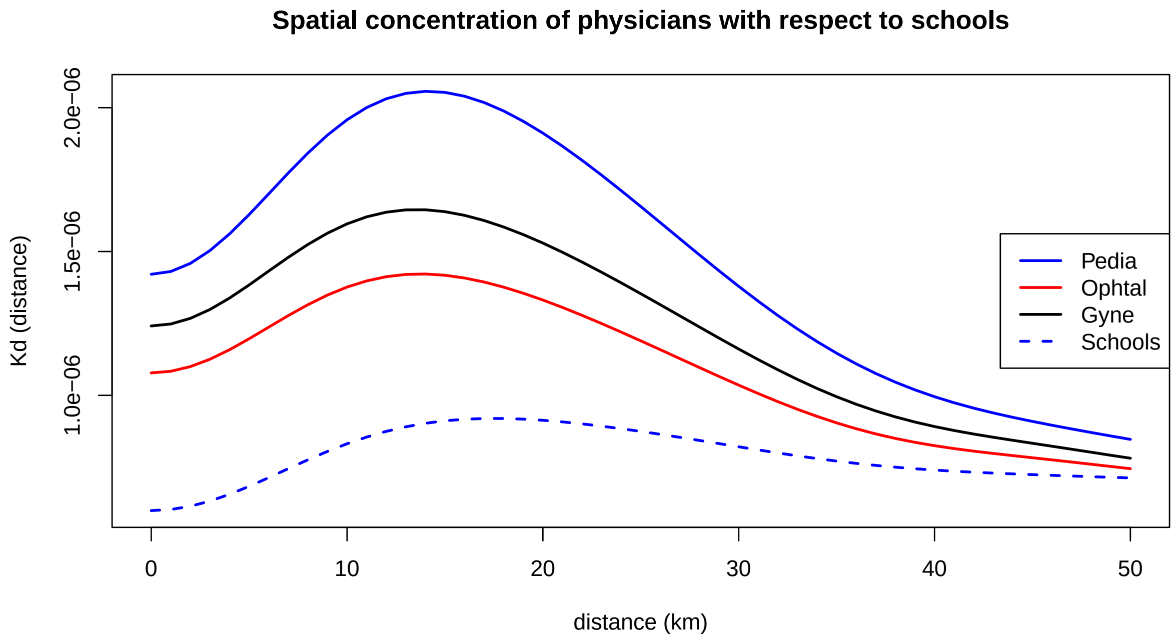


Figure K.4: Free-billing physicians

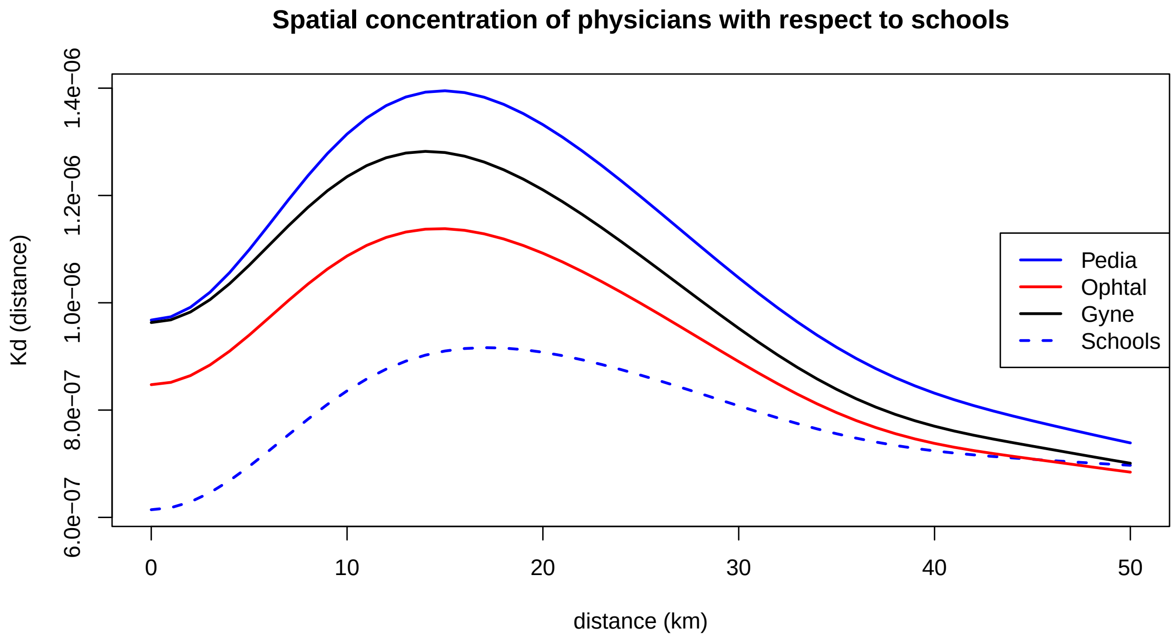


Figure K.5: All physicians (free-billing and regulated-fee)

L Robustness check

L.1: Sensitivity to mismeasurement

This table compares the reduced-form estimation results of our model of competitive and social interactions, using two measures of δ_i (the share of consultations performed at regulated fees). For each variable, the first line presents the reduced-form coefficients derived from $\hat{\hat{\delta}}_i$ (baseline model), while the second line displays the estimates obtained using $\hat{\hat{\delta}}_i(a)$. Please refer to Section 6.2 and Table 7 for additional details.

Model	Variable	Pedia	Ophthal	Gyneco
Endogenous profit factors (V_i)	$\delta_i P_F$	0.120^{***}	0.049^{***}	0.047^{***}
		0.115^{***}	0.044^{***}	0.042^{***}
	$(1-\delta_i)g(P_i)$	-0.058	0.027^{**}	-0.033^{**}
		-0.057	0.028^{**}	-0.034^{**}
Exogenous demand factors (Z_i)				
Patient base (20 KM)	Pop	-0.273	0.857	1.622^{**}
		-0.434	0.872	1.697^{**}
	Income	-0.181	-2.023^{**}	-2.028^{***}
		-0.214	-2.225^{***}	-2.058^{***}
	CMUC	-0.540	2.995	-0.199
		0.742	3.070	-0.292
Individual traits and practice	Gender	-0.131	0.174	-0.181
		-0.164	0.175	-0.191^{*}
	Experience	-0.402^{**}	-0.254	-0.163
		-0.395^{**}	-0.253	-0.164
	Multisite	-0.306	-0.206^{**}	-0.134
		-0.323	-0.201^{**}	-0.134
	Type1	0.519	0.654^{***}	0.137
		0.440	0.660^{***}	0.130
	Type2	-0.563^{***}	0.211	0.139
		-0.573^{***}	0.199	0.135
	Type3	-0.240	0.109	-0.179
		-0.273	0.098	-0.168
	Price gap	-0.081^{***}	-0.053^{***}	-0.074^{***}
		-0.083^{***}	-0.056^{***}	-0.075^{***}
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.405	0.550	1.042^{**}
		0.399	0.600	1.055^{**}
	$W_i^{CF}(\mathbf{1_n}-p)$	-1.253	-1.001	-0.770
		-1.510	-0.455	-0.791
	$W_i^{GF}(p-\frac{1}{2}\mathbf{1_n})$	2.892^{***}	3.788^{***}	2.845^{***}
		2.152^{***}	3.719^{***}	2.638^{***}
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.153	0.681	0.473
		0.399	0.193	0.485
Information and Statistics	N	994	2660	3055
	LL	-462.97	-693.29	-1191.99
		-464.00	-694.88	-1195.60
	Threshold (Km)	10	20	14
	NUTS3 F.E.	YES	YES	YES

Note: Constant terms are omitted. NPL estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table L.1: Estimation of the reduced-form model for the three specialties with different $\hat{\hat{\delta}}_i$

L.2: Sensitivity to change in weighting distance function

Model	Variable	Baseline	More convex	Less convex
		Gynecologists		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	1.042^{**}	0.994^{**}	1.096^{*}
		(0.534)	(0.486)	(0.595)
		0.140	**0.133**	**0.147**
	$W_i^{CF}(\mathbf{1_n} - p)$	-0.770	-0.715	-0.862
		(0.702)	(0.618)	(0.824)
		0.096	**0.089**	**0.108**
	$W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$	2.845^{***}	2.826^{***}	2.867^{***}
		(0.455)	(0.459)	(0.450)
		0.356	**0.353**	**0.358**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.473	0.436	0.535
		(0.626)	(0.541)	(0.609)
		0.059	**0.054**	**0.067**
Information and Statistics	LL	-1191.99	-1191.83	-1192.17
	Threshold (Km)	14	14	14
		Ophtalmologists		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.550	0.491	0.626
		(0.379)	(0.342)	(0.423)
		0.044	**0.056**	**0.050**
	$W_i^{CF}(\mathbf{1_n} - p)$	-1.001	-1.419	-0.379
		(2.189)	(1.817)	(2.672)
		0.074	**0.105**	**0.028**
	$W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$	3.788^{***}	3.729^{***}	3.851^{***}
		(0.605)	(0.612)	(0.593)
		0.279	**0.275**	**0.284**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.681	1.069	0.010
		(2.026)	(1.661)	(2.502)
		0.050	**0.079**	**0.001**
Information and Statistics	LL	-693.29	-693.13	-693.40
	Threshold (Km)	20	20	20
		Pediatricians		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.405	0.393	0.407
		(0.288)	(0.265)	(0.314)
		0.072	**0.087**	**0.072**
	$W_i^{CF}(\mathbf{1_n} - p)$	-1.253	-0.993	-1.671
		(1.335)	(1.222)	(1.470)
		0.194	**0.154**	**0.259**
	$W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$	2.892^{***}	2.901^{***}	2.878^{***}
		(0.478)	(0.481)	(0.475)
		0.448	**0.450**	**0.446**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.153	-0.004	0.449
		(1.145)	(1.035)	(1.278)
		0.024	**-0.001**	**0.070**
Information and Statistics	LL	-462.97	-463.11	-462.83
	Threshold (Km)	10	10	10

Note: Constant terms are omitted. Standard errors in parentheses. Marginal effects in bold. NPL estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table L.2: Reduced form model (7) with different W^{CF} and W^{CFR}

L.3: Sensitivity to change in social matrix definition

Model	Variable	Baseline	NUTS2	NUTS3 (het weights)
		Gynecologists		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	1.042^{**}	1.111^{**}	0.975^{*}
		(0.534)	(0.562)	(0.510)
		0.140	**0.140**	**0.131**
	$W_i^{CF}(\mathbf{1_n} - p)$	-0.770	-0.552	-0.731
		(0.702)	(0.723)	(0.685)
		0.096	**0.070**	**0.091**
	$W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$	2.845^{***}	-0.952	2.347^{***}
		(0.455)	(2.876)	(0.539)
		0.356	**-0.120**	**0.294**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.473	0.262	0.442
		(0.626)	(0.649)	(0.609)
		0.059	**0.033**	**0.055**
Information and Statistics	LL	-1191.99	-1197.83	-1193.62
		Ophtalmologists		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.550	0.728	0.515
		(0.379)	(0.462)	(0.379)
		0.044	**0.056**	**0.041**
	$W_i^{CF}(\mathbf{1_n} - p)$	-1.001	0.076	-1.162
		(2.189)	(2.590)	(2.119)
		0.074	**-0.006**	**0.086**
	$W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$	3.788^{***}	8.851^{***}	3.161^{***}
		(0.605)	(2.042)	(1.085)
		0.279	**0.653**	**0.234**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.681	-0.358	0.8310
		(2.026)	(2.159)	(1.962)
		0.050	**-0.026**	**0.061**
Information and Statistics	LL	-693.29	-692.17	-695.24
		Pediatricians		
Networks interactions	$W_i^{CFR}\mathbf{1_n}$	0.405	0.546	0.441
		(0.288)	(0.342)	(0.282)
		0.072	**0.087**	**0.078**
	$W_i^{CF}(\mathbf{1_n} - p)$	-1.253	-0.866	-1.290
		(1.335)	(1.488)	(1.307)
		0.194	**0.136**	**0.200**
	$W_i^{GF}(p - \frac{1}{2}\mathbf{1_n})$	2.892^{***}	1.969^{**}	2.524^{***}
		(0.478)	(0.881)	(0.526)
		0.448	**0.309**	**0.392**
Network centrality	$W_i^{CF}\mathbf{1_n}$	0.153	-0.245	0.194
		(1.145)	(1.301)	(1.124)
		0.024	**-0.039**	**0.030**
Information and Statistics	LL	-462.97	-467.72	-464.22

Note: Constant terms are omitted. Standard errors in parentheses. Marginal effects in bold. NPL estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table L.3: Reduced form model (7) with different W^{GF}

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