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Topics in Industrial Organization applied to Competition Policy

Thèse de doctorat de l'Université Paris-Saclay
préparée à l'École Polytechnique

École doctorale n°578 Sciences de l'Homme et de la Société (SHS)
Spécialité de doctorat : Sciences économiques

Thèse présentée et soutenue à Paris, le 12 septembre 2019, par

Thomas Larrieu

Composition du Jury :

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Notice

The three chapters of this dissertation are self-contained research articles. Therefore, the terms “paper” or “article” are used and parts of the content may be repeated. The last chapter is coauthored with Marie-Laure Allain.

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Summary

This thesis is composed of 3 essays in industrial organization applied to competition policy.

The Internet technology and the web economy create new types of markets and new relationships between market players. The majority of these new markets can be associated to platforms where two or more sides of the same market meet. Such “multi-sided” industries raise specific issues. Determining the optimal pricing strategy for both the platform and the users selling goods through the platform is one of the main challenges of this new economy. The first two chapters of my thesis analyze a contractual constraint on prices called Price Parity Agreement (PPA) from a theoretical and an empirical point of view.

Price Parity Agreements, also called Most Favoured Nation clauses, have recently drawn the attention from competition agencies throughout the world. In April 2012, the US department of Justice filed an antitrust lawsuit against HaperCollins, Hachette, Simon & Schuster, Macmillan, Penguin and Apple because they conspired to limit the freedom of e-book retailers to compete on retail prices. Publishers were blamed for taking the control on pricing decisions, substantially increasing the prices that consumers paid for e-books. In March 2016, the Supreme Court rejected Apple's final appeal. Apple was thus sentenced to pay \$450 millions to victims. At the same time, the European Commission opened a parallel investigation in December 2011. Publishers and Apple agreed to stop all existing so called agency contracts that provided restrictions on retail prices. In December 2012, the Commission concluded that the commitments were able to restore and preserve competition in the retail prices of digital books.

In spring 2015, the French, Swedish and Italian competition authorities accepted the commitments offered by Booking.com (April 2015[3]) and Expedia Inc. (June 2015), which for a period of five years would remove any Price Parity Agreements restricting price differentials between Online Travel Agencies (OTAs). On August the 6th of 2015, the French Parliament passed a law that banned all agreements placing restrictions on hotel pricing.

In the case of online booking platforms, PPAs refer to agreements between the platform and the hotel that regulates the price and/or supply conditions for the third party, the final consumers, who are not part of the agreements. PPAs are a specific type of agreement that are imposed by platforms to hotels. They are not vertical agreements in the strict sense, because platforms acts as intermediaries, but they have an inherent vertical element. Hotels reservation platforms such as Booking.com, Expedia and HRS incorporated PPAs into their general terms and conditions. Under these conditions, if an hotel wants to be displayed on Booking.com, it has to offer its rooms on this platform at the best prices available on any channel, at the best conditions. If we consider a hypothetical hotel that already offers 10 Queen bedrooms at a rate of 100 euros per rooms, Booking.com or any other platform using PPAs will require to have the same conditions of prices and capacities for the same type of rooms.

The first chapter studies PPAs from a theoretical point of view. It contributes to the existing literature by providing a new theoretical framework to analyse the effects of MFN clauses on competition and welfare depending on the bargaining power of hotels and platforms. The main novelty of my research is to account for balanced bargaining powers between platforms and hotels while setting the commission fees using a Nash-in-Nash solution concept. The main contribution of this research to the literature is to show that MFN clauses are detrimental to consumers if platforms have most of the bargaining power, which is aligned with the current literature and the views of competition policy authorities. However, MFN clauses lead to lower prices and higher consumer surplus when hotels have most the bargaining power and the competition between hotels is high. Thus, accounting for different bargaining power between hotels and platforms allows to highlight the existence of cases where MFN clauses are beneficial to the economy. This result is all the more important that small and big hotel chains are in direct competition and don't have the same bargaining power with respect to platforms.

The second chapter of my thesis provides an empirical analysis of the effects of the removal of PPAs. From April 2014 (16 months before the end of PPAs) to July 2017 (24 months after the end of PPA), I collected the daily listed prices of a panel of 863 hotels on Kayak.com, Booking.com and Google Hotels. In addition, I collected individual information of each hotel (quality, number of rooms, services...) on TripAdvisor.com. As the removal of PPA affected simultaneously all hotels in France, and several other countries in Europe, I analyze the effects of this removal using a before and after design. The major limitation of this method is the risk of omitted variable bias (see Pearl (2009)[28]). To avoid omitting explanatory factors I use several control variables. I first control for external shocks in demand using public data on the number of effective nights booked in Paris. I also control for the entry of Airbnb as a direct competitor of the hotel industry using the number of search request for "Airbnb Paris" on Google.

I demonstrate the empirical effects of PPAs on 3 aspects of hotels' pricing strategy: (i) the average level of price, (ii) the price discrimination across platforms and (iii) the inter-temporal price discrimination. I show that the end of PPAs imposed by public authorities to online travel agencies (OTAs) in France leads to a decrease of about 3.1% to 4.5% in the average level of hotels' prices, an increase of about 2.3% to 1.43% of the dispersion of prices across platforms and an increase of about 3.6% to 2.1% in the degree of inter-temporal price discrimination. Thanks to our unique dataset, this paper provides the first empirical study of the impact of the drop of PPAs on the average level of hotels' prices in Paris and contributes to the growing literature analysing the effects of PPAs on prices. Moreover, to the best knowledge of the author, this article is the first to empirically study the impact of PPAs on price discrimination strategies.

The last chapter of my thesis is not linked with PPAs but with one of the major objectives of competition policy which is to deter the formation of cartels. In this chapter, Marie-Laure Allain and myself focused on the analysis of the financial fines imposed by the French Autorité de la Concurrence to cartels in France between 2006 and 2018. We build a unique dataset of all fines decided by the Autorité de la Concurrence with regards to 466 firms and bring an estimation of the price elasticities for about the half of the firms. We show that the level of these fines is sub-optimal and doesn't meet the deterrence objective in the majority of the cases. Furthermore, the fines also appear too low to ensure the restitution of illicit profits by cartel members.

Chapter 1

Most Favoured Nation Clauses on the Online Booking Market

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Abstract

We show that Most Favoured Nation clauses on the online booking market are detrimental to consumers if platforms have most of the bargaining power. They attenuate competition between platforms, lead to higher commission fees and higher hotel rooms' prices. However, MFN clauses may also be welfare improving by leading to lower commission fees and higher consumer surplus when hotels own the bargaining power and competition between them is high. This paper shows that the balance between the bargaining power of hotels and platforms is as a key element in assessing the competitive effects of MFN clauses.

Keywords: Most Favoured Nation Clause, Across Platform Parity Agreements, Online Booking Platforms, Vertical agreements, Bargaining.

JEL Classification: L13, L42, K21, D43

1.1 Introduction

Competition enforcers are increasingly confronted with MFN clauses in various sectors such as the online sales sector for e-books and ebooks², the e-commerce sector where Amazon Market place set MFN clauses in the United Kingdom and Germany³, and for insurance comparison sites in the United Kingdom⁴. Given the rapid growth of e-commerce and online-platforms in particular, MFN clauses have a significant potential for distorting competition between distribution channels. These developments have stimulated a lively debate about the competition assessment of MFN clauses that has resulted in an increasing number of contributions on this topic (see the OECD hearing[19] on the subject).

In spring 2015, the French, Swedish and Italian competition authorities accepted the commitments offered by Booking.com (April 2015[3]) and Expedia Inc. (June 2015), which for a period of five years would remove any MFN clauses restricting price differentials between Online Travel Agencies (OTAs). On August 8 2015, the French Parliament passed a law (Loi Macron) that banned all agreements between hotels and OTAs placing restrictions on hotel pricing. This ban includes both narrow and broad agreements and goes beyond the commitment offered by Booking.com and accepted by the French Competition Authority.

In the context of sellers who sell their products through intermediary platforms, MFN clauses, also known as Price Parity Agreements, are contractual restrictions requiring that a particular seller will not sell at a lower price through a platform or any channel other than the one with which it has the MFN agreement. While the literature on MFN clauses (wholesale tariffs offered by a supplier to different retailers) is broad since 1980 (see Hviid (2010) [13]), the focus on the competitive effects of MFN clauses on online platforms is more recent and still growing.

²See decision in the United States v. Apple Inc., 952 F. Supp. 2d 638, 15 647 (S.D.N.Y. 2013).

³Commission accepts commitments from Amazon. Decision is available at: http://europa.eu/rapid/press-release_IP-17-137_en.htm

⁴CMA's decision is available at: <https://www.gov.uk/cma-cases/private-motor-insurance-market-investigation>.

One of the first paper of this literature is Gans (2012) [11]. He examines the pricing strategy of mobile applications when application providers can either supply consumers directly or through a mobile platform (such as a smart phone or tablet). He shows that in this context, most favoured customer clauses can allow the platform provider to earn more profits and may help to solve a holdup problem. But the literature also shows that MFN clauses can be detrimental to consumers. Boik and Corts (2016) [12] consider the effect of MFN clause on a traditional vertical setting where a monopoly sells its products through two retailers. They show that MFN clauses can lead to higher fees, prices and retailers profit. It can also deter the entry of low end firms. Johnson (2017)[20] extends this model from a monopoly to multiple suppliers and shows that imposing price agreement reduce the competition between platform by cutting their incentive to reduce fees. Wang and Wright (2016)[25] reach the same conclusion by adding consumers search and showrooming. They provide a model in which consumers search for firms directly or through platforms. Platforms lower search costs but charge firms for the transactions they facilitate. They show showrooming helps to constrain the platform's fees and is good for consumers, and by reducing showrooming, MFN clauses suppress competition between selling channels. In addition, Johansen and Vergé (2017)[19] show that when one allows each supplier to sell either through a platform or directly to consumers, whether price parity clauses lead to higher or lower commissions depends on the degree of competition between the suppliers. In particular, they find that MFN clauses may simultaneously lead to higher profits for platforms and suppliers, and increase consumer surplus. This result is mainly driven by the ability of hotels to substitute sales through platform with direct sales. It needs to be mitigated by the empirical findings of Cazaubiel, Cure, Johansen and Vergé (2018)[4] who show that the direct selling channel of the hotel is not a substitution channel but rather a complementary channel compared to online platforms.

This paper directly contributes to this growing literature on online platforms by providing a new theoretical framework to analyse the effects of MFN clauses on competition and welfare depending on the bargaining power of hotels and platforms. The main novelty of our paper is to account for balanced bargaining powers between platforms and hotels while setting the commission fees using a Nash-in-Nash solution concept. In the first step of the game, hotels and platforms negotiate the fees in four bilateral negotiations that are secret and simultaneous. We consider that both hotels have the same bargaining power regarding platform and *vice versa*. In the second step of the game, hotels simultaneously set final prices. This first framework constitutes the no-restriction setting. In a second time we constraint hotel with MFN clauses by imposing that the price set on one platform should be the same on the other platform.

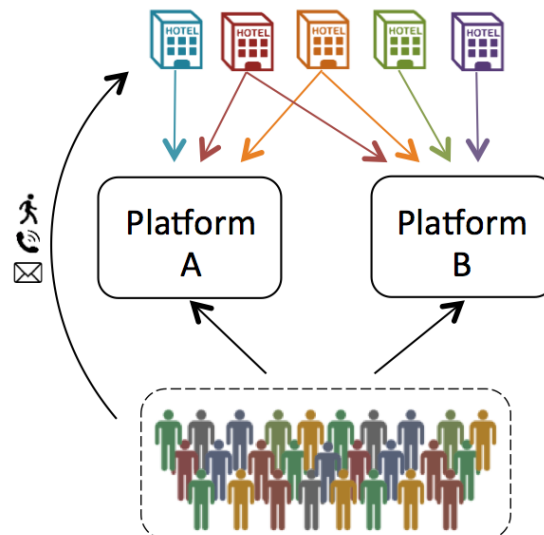
The main contribution of this article to the literature is to show that MFN clauses are detrimental to consumers if platforms have most of the bargaining power, which is aligned with the current literature and the views of competition policy authorities. However, MFN clauses lead to lower prices and higher consumer surplus when hotels have most the bargaining power and the competition between hotels is high. Thus, accounting for different bargaining power between hotels and platforms allows to highlight the existence of cases where MFN clauses are beneficial to the economy. This result is all the more important that small and big hotel chains are in direct competition and don't have the same bargaining power with respect to platforms.

The online booking market is described in more details in section 1.2. The model is presented in section 1.3. In section 1.4 and 1.5 we analyse the effects of MFN clauses on commission fees and prices. Finally we explore possible extensions of the model in section 1.5 and conclude in section 1.6.

1.2 The online booking industry

The online hotel booking industry is a market with network externalities. Booking platforms bring value to both hotels and consumers by reducing the cost of search. The more a platform gather hotels the higher will be the value for the consumers. And reciprocally, hotels will be more attracted by a platform with a large consumer base. Rochet and Tirole (2003)[22]) states that most markets with network externalities are two-sided markets. They describe how these platforms need “get both sides of the market on board” by setting the good incentives while making money overall.

Graph 1: The Online Booking Market



On one side of the market consumers are looking for hotels, usually in a specific area for a specific date. Consumers have two main choices, either to go directly to the hotel (by phone, email or walking directly to the front desk) or to choose their hotel on a platforms offering booking services, typically referred to as Online Travel Agencies (OTAs) that usually provide three separate services to consumers: price comparison, search facility and product review. Consumers can choose to go on one or several platforms. If consumers go on only one platform (because of habits, fidelity rebates, etc.) they are considered as single-homing users. If they are not affiliated to one specific platform and usually go on several platforms to choose their hotel they are considered as multi-homing users. Price comparison websites such as Kayak.com or Tripadvisor.com tend to facilitate the ability of users to multi-home. On the other side of the market, hotels sell rooms to consumers either using offline channels only (phones, walk-in, mail, etc.) or by being displayed online on one or several OTAs. Hotels pay a commission fee proportional to the price to the platform for each room sold by this latter.

Hotels use booking platforms to be displayed online to a vast amount of customers 24/7 in more than 200 different countries⁵. In Europe, these platforms represent the main channel for online bookings. They account for about 70% of online hotel bookings, the remaining 30% being booking made directly on the hotel's website or by phone. For a hotel, it is essential to be present on these platforms: *"they ensure great visibility and are widely used by Internet users all over the world"*⁶.

⁵Booking.com claims to have hotels' rooms from about 224 countries. See: www.booking.com

⁶See report of Autorité de la Concurrence on the Booking.com case[3]

The 2 major platforms on this market are Priceline Groupe (Booking.com) and Expedia. Priceline Group regroups several websites such as Booking.com, Kayak.com, Agoda.com or Rentalcars.com. In 2015 the turnover of Priceline Groupe was about 9.22 billion \$ for an operational margin of 35.5%⁷. Booking.com is the biggest online booking platform. It claims to have over 700,000 properties globally under contract and to deal with more than 900,000 room reservations each day. In 2013, Booking.com accounted for more than two thirds of Priceline's revenue. On the other hand, Expedia also owned travel websites such as Hotels.com, Trivago.com, Howeway.com or Venere.com. Its turnover in 2015 was about 6.7 billion \$.

Most Favoured Nation clauses are set on this market by platforms. MFN clauses are agreements between the platform and the hotel that regulates the price and/or supply conditions for the third party, the final consumers, who are not part of the agreements. MFN clauses are a specific type of agreement. They are not vertical agreements in the strict sense, because platforms act as intermediaries, but they have an inherent vertical element, as they involve and affect players that operate at different levels of the value chain.

In the hotel reservation sector, hotels reservation platforms such as Booking.com, Expedia and HRS incorporated MFN clauses into their general terms and conditions at their creation. Under these conditions, if a hotel wants to be displayed on Booking.com, it has to offer its rooms on this platform at the best prices available on any channel, at the best conditions. If we consider a hypothetical hotel that already offers 10 rooms with a view on the sea at a rate of 100 euros per room, Booking.com or any other platform with MFN clauses will require to have at least these same conditions.

⁷See Priceline Financial Reports : <http://ir.pricelinegroup.com/financials.cfm>

A distinction has been made by competition authorities between narrow and broad agreements. A narrow agreement between a hotel and a OTA commits the hotel not to charge a lower price on its own distribution channels than the one charged by the OTA to consumers. Under these agreements, our hypothetical hotel is not able to offer better prices or conditions to someone who makes a reservation offline. The price and conditions between OTA and the direct channels of the hotel have to be the same or better on the OTA. In contrast, a broad (or wide) agreement between a hotel and a OTA commits a hotel not to charge a lower price on competing OTAs. Under these agreements, the hotel has to put the exact same prices and conditions on every booking platform.

In the following we will mainly consider the MFN clauses on prices and conditions without looking precisely on MFN clauses on capacity.

1.3 The model

The Setup

Consider two hotels i and j , both sell homogeneous rooms on the market through platforms. Hotels cannot sell their rooms directly to consumers, they have to be distributed through platforms only. They set the price of rooms to be offered by each platform to consumers.

Consider also two platforms K and L distributing rooms to consumers. To access the services of platform K , the hotel i has to pay a per unit commission fee f_{iK} . This fee is due to the platform each time i sells a room through platform K .

The following model, build on Allain and Chambolle (2011)[1], integrates the competition between hotels and the competition between platforms. Because the coexistence of both level of competition makes the solving with a general demand function tedious (see Shaffer, 1991)[23]), we consider a linear specification. The inverse demand function of the price p_{iK} of a room from the hotel i sold through platform K is:

$$p_{iK} = 1 - q_{iK} - aq_{jK} - bq_{iL} - cq_{jL}$$

Parameter $a \in]0, 1[$ measures the substitution rate between the two hotels on the same platform (hotel competition): hotels i and j become closer substitutes on the same platform when a increases, while when a close to zero the demand for the two hotels is independent. Parameter $b \in]0, 1[$ represents the degree of substitutability for the same hotel's room between both platforms (platform competition). When b close to zero, each consumer only goes to one platform to find a hotel room (single-homing). When b increases, more and more consumers multi-home, they have a look on both platforms to compare hotels. Finally, parameter c is the degree of cross-substitutability between the two hotels on different platforms. We assume that $c = a.b$ ⁸.

The timing of the game is as follows:

- Stage 1: Platform K and hotel i negotiate a per unit commission fee that the hotel i will pay to the platform K each time a room is sold by that platform. The four bilateral negotiations are secret and simultaneous. Success or failure of the negotiations and the commission fee negotiated are only observable by the hotel and the platform involved in the negotiation. Stage 1 ends when the four negotiations have led to either an agreement or a breakdown. The bargaining process is detailed in section 3.2.
- Stage 2: Hotel i and j select on which platform to be listed and simultaneously set final prices p_{iK} and p_{iL} .⁹ Without any restriction, hotels are able to make available the same type of rooms at different prices on different platforms. Each hotel can choose, depending on the fees charged by each platform, to be listed on both platforms or to exit this platform and single home on the other platform. During the first stage, platforms take into account this possible threat of an hotel leaving its platform for its competitor.

⁸The underlying assumption is that a representative consumer has a quadratic utility function and a budget of 1 (see Dobson and Waterson, 1996[7]). Assuming $c = a.b$ is sufficient for the utility to be concave: the substitutability between products K_i and L_j is a combination between intra- and inter-brand substitution. Choosing another value for c such that the utility function is concave would not qualitatively alter our results.

⁹The choice between price competition rather quantity competition is discussed in Section 7

Bargaining assumptions and solution concept

To avoid equilibrium existence issues (See Rey and Vergé (2010)[20]), we use the contract equilibrium concept formalized by Crémer and Riordan (1987)[6]. To account for balance bargaining power we indeed use the Nash and Nash solution concept (see Allain & Chambolle (2011)[1] and Collard-Wexler, Gowrisankaran and Lee (2017)[5]). Formally, this solution concept boils down to making the following assumptions.

The fees are determined through a Nash bargaining in which the hotel's bargaining power is $\alpha \in [0, 1]$ and the one of the platform is $(1 - \alpha)$. Note that both platforms have the same bargaining power with respect to the hotels, such as hotels with respect to platforms¹⁰.

We assume that the fee f_{iK} offered by the platform K to the hotel i on stage 1 is not observable by others and that the outcome (success or not) of the negotiation between the hotel and the platform is also not observable. However, in stage 2, consumers have a perfect information on the availability and price of every hotels on every platforms when making their choice. This hypothesis of non-observability is discussed in section 6.

We look for symmetric, subgame-perfect *Contract Equilibria* in pure strategies. In a Contract Equilibrium, firms have passive beliefs. If a hotel receives an unexpected offer from a platform, his belief about the other contract negotiations, including the one it has with the other platform, would not change. Furthermore, this equilibrium concept does not consider multilateral deviations. In other words, we assume that each hotel and platform send a different agent to each contract negotiation and that two agents of a given firm cannot communicate with each other while negotiating.

¹⁰In other words, we assume that hotels have almost the same size and market power. This is a strong assumption since we know that many different types of hotels can be found on OTA, from the independent hotel to the major company managing dozens of hotels. We discuss this hypothesis in the conclusion but although it is strong, it still allows to analyze the effects of MFN clauses on a country where hotels are concentrated around big groups (Germany for instance) compared to a country where the majority of hotels are small independent ones (France)

In the following we first solve this game without imposing any restrictions on the way hotels can set the final price of their rooms. In a second time, we impose hotels to set the same price of rooms on both platforms as if MFN clauses were active. We will focus on symmetric equilibrium where each of the 2 hotels is listed on both platforms.

1.4 Benchmark : No Restriction

In this section we present the benchmark case without any legal restriction on the price of rooms set by hotels. Hotels can set different prices on different platforms.

Stage-2

Consider the stage-2 of the game. Hotel i knows the outcome of its two negotiations from stage 1 but cannot observe the outcome of the negotiations between the hotel j and the platforms K and L .

Assume the four negotiations succeeded in stage 1. Both hotels are present on both platforms. In stage 2, the hotel i sets prices p_{iK} and p_{iL} so as to maximize the following profit:

$$\pi_i = D_{iK}(p_{iK}, p_{iL}, p_{jK}^a, p_{jL}^a)(p_{iK} - f_{iK}^*) + D_{iL}(p_{iK}, p_{iL}, p_{jK}^a, p_{jL}^a)(p_{iL} - f_{iL}^*)$$

where f_{iK}^* and f_{iL}^* are the observed outcomes of hotel i 's negotiations with platforms K and L , and p_{jK}^a and p_{jL}^a the price of the hotel j on platforms K and L anticipated by the hotel i .

Assuming correct anticipations, the two best response final prices of each hotel i and j are:

$$p_{iK}^{BR}(p_{jK}^a, f_{iK}^*) = \frac{1 + f_{iK}^* - a(1 - p_{jK}^a)}{2}$$

Where p_{jK}^a is the anticipated price set by the hotel j on platform K .

Lemma 1 *The intersection of the best responses gives the subgame equilibrium prices*

denoted p_{iK}^e :

$$p_{iK}^e(f_{iK}^*, f_{jK}^*) = \frac{2(1 + f_{iK}^*) + af_{jK}^* - a(1 + a)}{4 - a^2} \quad (1.1)$$

Where f_{iK}^* represents the public output fee of the negotiation between the hotel i and the platform K . Final prices p_{iK}^e increase in f_{iK} and f_{jK} and are independent of f_{iL} and f_{jL} .

Proof. see Appendix A.1 ■

Stage-1

Consider now the stage 1 where each hotel will negotiate the level of commission fees he is willing to accept to sell his rooms through the platform. The Nash program of the negotiation between the platform K and the hotel i is:

$$\max_{f_{iK}} (\pi_i^a - \pi_i^{st})^\alpha (\pi_K^a - \pi_K^{st})^{(1-\alpha)}$$

where π_i^a (resp. π_K^a) is the anticipated profit of the hotel i (resp. platform K) and π_i^{st} (resp. π_K^{st}) is the anticipated status-quo profit earned by the hotel i (resp. K) if the negotiation breaks, i.e if i decides to only make his rooms available on the other platform L , all other negotiations being successful.

To define the status-quo profits, assume for instance that the negotiation between hotel i and platform K fails. 3 goods are for consumers to purchase. Because the outcome of the negotiation is secret, only i and K anticipate the changes in demand functions coming from the absence of the hotel i on platform K .

Demand functions change to:

$$D_{iL}^{st}(p_{iL}^{st}, p_{jL}^a) = \frac{1 - p_{iL}^{st} + a(p_{jL}^a - 1)}{1 - a^2} \quad (1.2)$$

$$D_{jK}^{st}(p_{jK}^a, p_{jL}^a) = \frac{1 - p_{jK}^a + b(p_{jL}^a - 1)}{1 - b^2} \quad (1.3)$$

Where p_{jL}^a, p_{jK}^a are the prices set by the hotel j not knowing that negotiation failed anticipated by the hotel i and p_{iL}^{st} is the status-quo price set by the hotel i

on platform L if the negotiation with K failed. The status-quo equilibrium price of the hotel i is the solutions of the profit maximization program:

$$\max_{p_{iL}}(\pi_i^{st}) = D_{iL}^{st}(p_{iL}, p_{jL}^a)(p_{iL} - f_{iL}^a)$$

Leading to the status-quo price:

$$p_{iL}^{st}(f_{iL}^a, f_{jL}^a) = \frac{2(1 + f_{iL}^a) + af_{jL}^a - a(1 + a)}{4 - a^2}$$

Where f_{iL}^a, f_{jL}^a are the fees set by platform L anticipated by the hotel i . Note that $p_{iL}^{st} = p_{iL}^e$, the optimal price of the hotel i is the same whether it is present on platform K or not. This property holds for any linear demand function with symmetric cross-price derivatives.

The status-quo profits anticipated by the negotiating firms are then:

$$\pi_i^{st} = D_{iL}^{st}(p_{iL}^{st}, p_{jL}^a)(p_{iL}^{st} - f_{iL}^a)$$

$$\pi_K^{st} = D_{jK}^{st}(p_{jK}^a, p_{jL}^a)f_{jK}$$

The subgame equilibrium outcome of the negotiations is given by the solution of the four Nash programs:

$$\max_{f_{iK}}(\pi_i^a - \pi_i^{st})^\alpha (\pi_K^a - \pi_K^{st})^{(1-\alpha)}$$

Proposition 1 *In equilibrium the fees are:*

$$f_{iK}^* \equiv -\frac{(a+2)(\alpha-1)(b-1)}{\alpha(a(a+1) - (a+2)b) + a(a+b-1) + 2(b-2)} \quad (1.4)$$

Proposition 2 *And final prices are:*

$$p_{iK}^* = \frac{2(f_{iK}^* + 1) - a(f_{iK}^* + 1 + a)}{4 - a^2} \quad (1.5)$$

The no-restriction equilibrium fees f_{iK}^* and room prices p_{iK}^* strictly increase with the bargaining power of platforms (α going to zero).

Consider the stage 1 of the game while fees are negotiated between the hotel i and platform K . The joint profit of the hotel and the platform is maximum when commission fees are equal to zero. When hotels have all the bargaining power ($\alpha = 1$), the platform gets zero ($f_{iK}^* = 0$), and the hotel receives the maximum profit. When platforms gain bargaining power (α decreases), the platform claims a share of joint profit and the fee increases. As a consequence, joint profit may decrease because of double marginalization, but the platform gets a larger share of a smaller pie.

Proposition 3 *The no-restriction equilibrium fees f_{iK} and room prices p_{iK} strictly increase in a (competition between hotels) and decrease in b (competition between platforms).*

The parameter b represents the platform competition. With b close to zero, each platform faces a demand from captive consumers. When buying a hotel room, the representative consumer goes to one of the two platforms without looking at the other before booking a room. In that case, hotels have to be present on both platforms to address the whole market. Thereby in case of a breach in negotiations between hotel i and platform K , i benefits from little, if any, increase in demand on the rival platform L , and the hotel loses all the consumers of platform K . The difference between the profit of the hotel with and without a breach in negotiation is thus very high. The hotel has a lot to lose if the negotiation breaks, its bargaining power is low. By contrast, most of the consumers that are looking for the hotel i on the platform K , stay on platform K and go to the hotel j . Hence, the platform is almost not affected by the loss of the hotel i as the demand shifts to the other hotel present on the platform. The platforms' market power is thus high and they capture a large share of the joint profit through a high fixed fee.

Conversely, when b is close to one, consumers see platforms as close substitutes and go on both platforms before selecting the right hotel. When hotel i decides to break negotiation with platform K and to be listed on platform L only, most of the consumers that were looking for this hotel shift to platform L . Hence i benefits from increased sales on platform L , that offsets the lost sales on K . This increasing competition between platforms gives more bargaining power to the hotel during the negotiation as its status-quo profit is close to the equilibrium profit. Therefore, the higher is b , the more hotels gain bargaining power and the lower are the equilibrium commission fees.

Consider now the role of hotel competition. Assume first that $a = 0$. Competition between hotels doesn't exist. Consumers are captive and go to only one of the two hotels. Assume negotiations between the hotel i and the platform K break. The platform can no longer display the hotel i and loses all the demand addressed by this hotel. The difference between the anticipated profit and the status-quo profit ($\pi_K^a - \pi_K^{st}$) of the platform is maximum and the hotel can thus claim a larger share of the bilateral profit. As a goes to 1, the degree of substitution between hotels increases. If negotiations between i and K break, a share (increasing in a) of the demand addressed by the hotel i is redirected to the hotel j on the same platform. The status-quo profit of the platform is close to its profit without a break in negotiation. Therefore, the difference between π_K^a and π_K^{st} is at its maximum when $a = 0$ and decreases to zero when a increases to one. With the difference of profit going down to zero with a , platforms gain bargaining power and are able to negotiate higher commission fees. Hence, the commission fees increase with the level of competition a .

1.5 Most Favoured Nation Clauses

Assume now that both platforms set MFN clauses. As a reminder, MFN clauses are contractual clauses that constraint the hotel to give to the platform that benefits from the clause at least the best price (the lowest) available on the market. In other words, if the hotel i offers rooms on platform K at a price $p_{iK} = 100$, and if the second platform L has set MFN clauses, the hotel has to offer rooms at a maximum price of $p_{iL} \leq p_{iK} = 100$ on platform L . When both platforms set MFN clauses, the hotel has to set the exact same price on both platforms. Let's write \bar{p}_{iKL} the same price set by the hotel on both platforms under MFN clauses.

In the following section we will solve the game under MFN clauses constraint assuming that both platforms set the clauses and we compare the results with the benchmark section to evaluate the impact of MFN clauses.

Note that the negotiations allow the hotel to escape from the MFN clauses by only be listed on one platform. Indeed, being listed on only one platform, the MFN clauses disappear since consumers can only book the hotel through one platform only.

Stage 2

Consider the stage-2 of the game, where the four commission fees $\bar{f}_{iK}, \bar{f}_{iL}, \bar{f}_{jK}, \bar{f}_{jL}$ set under MFN clauses are given. Assume the four negotiations succeeded in stage 1. Both hotels are present on both platforms and are constrained by the MFN clauses to set the same prices on both platforms. The profit of the hotel i under MFN clauses is:

$$\bar{\pi}_i = D_{iK}(\bar{p}_{iKL}, \bar{p}_{jKL}^a)(\bar{p}_{iKL} - \bar{f}_{iK}^*) + D_{iL}(\bar{p}_{iKL}, \bar{p}_{jKL}) (\bar{p}_{iKL} - \bar{f}_{iL}^*)$$

Where \bar{p}_{iKL} stands for the price of rooms set by the hotel i under MFN clauses on platform K and L and \bar{p}_{jKL}^a is the price of j on platform K and L anticipated

by i . The best response final price of hotel i is:

$$\bar{p}_{iKL}^{BR} = \frac{2 + \bar{f}_{iK}^* + \bar{f}_{iL}^* + 2a(\bar{p}_{jKL})}{4}$$

Lemma 2 *The intersection of the best responses gives the subgame equilibrium prices denoted*

$$\bar{p}_{iKL}^e(\bar{f}_{iK}^*, \bar{f}_{iL}^*, \bar{f}_{jK}^*, \bar{f}_{jL}^*) = \frac{4 + 2(\bar{f}_{iK}^* + \bar{f}_{iL}^*) + a(\bar{f}_{jK}^* + \bar{f}_{jL}^*) - 2a(1 + a)}{2(4 - a^2)} \quad (1.6)$$

Proof. See Appendix A.2 ■

Note that although the sub-game equilibrium price p_{iK}^e (see equation (1)) of hotel i offered on platform K absent of MFN clauses only depends on the fees f_{iK} and f_{jK} charged by platform K , under MFN clauses, the sub-game equilibrium price \bar{p}_{iKL}^e also depends on the fee charged by the rival platform, f_{iL} and f_{jL} .

Stage-1

Consider now the stage 1 of the game where each hotel will negotiate the level of commission fees he is willing to accept to sell his rooms through the platform. The Nash program of the negotiation between the platform K and the hotel i is the same than before except that the hotel can only set one price, the same on both platforms:

$$\max_{\bar{f}_{iK}} (\bar{\pi}_i^a - \bar{\pi}_i^{st})^\alpha (\bar{\pi}_K^a - \bar{\pi}_K^{st})^{(1-\alpha)}$$

where $\bar{\pi}_i^a$ (resp. $\bar{\pi}_K^a$) is the anticipated profit of the hotel i (resp. platform K) under MFN clauses and $\bar{\pi}_i^{st}$ (resp. $\bar{\pi}_K^{st}$) is the anticipated status-quo profit under MFN clauses earned by the hotel i (resp. K) if the negotiation breaks, all other negotiations being successful.

Assume a breakdown in negotiations between the hotel i and the platform K . Remember that the outcome of the negotiation is secret, only i and K can observe the output of the negotiation and can anticipate the absence of i on

platform K leading to:

$$\bar{D}_{iL}^{st}(p_{iL}^{st}, \bar{p}_{jKL}^a) = \frac{1 - p_{iL}^{st} - a(1 + \bar{p}_{jKL}^a)}{1 - a^2}$$

$$\bar{D}_{jK}^{st}(\bar{p}_{jKL}^a) = \frac{1 - \bar{p}_{jKL}^a}{1 + b}$$

Where \bar{p}_{jKL}^a is the anticipated price of by the hotel j , under MFN clauses, on both platforms K and L anticipated by the hotel i , and p_{iL}^{st} is the status-quo price set by the hotel i on platform K . Note that p_{iL}^{st} is no longer constrained by MFN clauses since in status-quo, the hotel i is only present on one platform. We then derived the subgame equilibrium outcome of the negotiations by the solving the four Nash programs :

$$\max_{f_{iK}} (\bar{\pi}_i^a - \bar{\pi}_i^{st})^\alpha (\bar{\pi}_K^a - \bar{\pi}_K^{st})^{(1-\alpha)}$$

Proposition 4 *In equilibrium under MFN clauses, the fees are:*

$$\bar{f}_{iK}^* \equiv \frac{2(a+2)(\alpha-1)(b-1)}{((a-2)a-6)(b-1) - 2\alpha(a^2 - (a+3)b + a - 1)} \quad (1.7)$$

Proof. See Appendix A.3 ■

Proposition 5 *By forcing the hotel to set the same price on both platforms, MFN clauses dampen competition between platforms.*

Compare the equilibrium price p_{iK}^e sets under no-restriction and \bar{p}_{iKL}^e sets under MFN clauses.

$$p_{iK}^e = \frac{2(1 + f_{iK}^*) + a f_{jK}^* - a(1 + a)}{4 - a^2}$$

$$\bar{p}_{iKL}^e = \frac{4 + 2(\bar{f}_{iK}^* + \bar{f}_{iL}^*) + a(\bar{f}_{jK}^* + \bar{f}_{jL}^*) - 2a(1 + a)}{2(4 - a^2)}$$

Under no-restriction the price set by the hotel i only depends on the fee charged by the platform K to both hotels (f_{iK}^*, f_{jK}^*) , while under MFN clauses, the price \bar{p}_{iKL}^e set on each platform depends on the fees charged by both platforms to both hotels $(\bar{f}_{iK}^*, \bar{f}_{iL}^*, \bar{f}_{jK}^*, \bar{f}_{jL}^*)$.

Now consider that platform K decreases hotel i 's fees. Under no restriction, i will respond by decreasing its price on this platform to benefit from a higher demand at a lower acquisition cost compared to the other platform. Under MFN clauses, if the hotel i wants to decrease its price on platform K , it should offer this same price on platform L . Hence, the decrease in price benefits to the platform which decreases its fee but also to its competitor. As price is the same on both platforms, few or no additional demand goes to the platform which decreases its fees.

Therefore, under MFN clauses, platforms have less incentive to decrease their fees, which decrease the competition level between platforms. This result is aligned with the findings of Johnson (2017)[20] who provides an analysis of vertical relations in markets with imperfect competition and shows that retail price-parity restrictions raise industry prices.

Lemma 3 *When platforms have all the bargaining power ($\alpha = 0$), the fee set under MFN clauses no longer varies with respect to the level of competition between platforms (b parameter) compared to the fees set under no restriction.*

The proof is straightforward, by setting α to zero in the equation 5 we have:

$$\bar{f}_{iK}^* = \frac{-2(a+2)}{(a-2)a-6}$$

Parameter b is absent from this equation and \bar{f}_{iK}^* is the same whatever the level of competition b between platforms.

With $\alpha = 0$, the bargaining power of the platforms is maximum and the negotiation phase is reduced to a take-it or leave-it offer from platforms to hotels. From Proposition 2 we know that under MFN clauses platforms have less incentive to decrease commission fees. Indeed, as under MFN clauses any decrease in the fee \bar{f}_K directly affects in the same proportion \bar{p}_{iL} and \bar{p}_{iK} , MFN clauses suppress platform competition. As a consequence, because the b parameter is the same for both platforms, the repartition of the demand between platforms is the same under MFN clauses which explains that the equilibrium fees \bar{f}_{iK}^* do no longer vary in b .

Finally, note that the difference between equilibrium fees set under MFN clauses \bar{f}_{iK}^* and the fees set under no-restriction f_{iK}^* increases in b . This comes from the no-restriction fee f_{iK}^* that decreases with the level of competition b whereas the fees under MFN clauses \bar{f}_{iK}^* are not affected by the parameter b . Thereby, the more platforms are in competition, the greater is the difference between high fees set under MFN clauses and low fees set without any restrictions. The higher b the more platforms have the incentive to set MFN clauses when $\alpha = 0$.

Corollary 1 *The level of fees set by platforms under MFN clauses when they own all the bargaining power ($\alpha = 0$) is higher than the fees they would have set if platforms were colluding.*

Proof. See Appendix A.4 ■

Under MFN clauses, platforms have a common interest in decreasing their fees. However, it is not profitable for each platform to decrease its fee alone because the decrease will affect the price set by the hotel and benefit to both platforms without giving a strategic advantage to the platform who decreases its fee. Thereby, each platform has a self interest in letting its competitor decrease its fee but not to decrease its own fee. Equilibrium fees are thus set above the collusive outcome that cannot be reached, which highlight the harm to the economy when platforms have all the bargaining power.

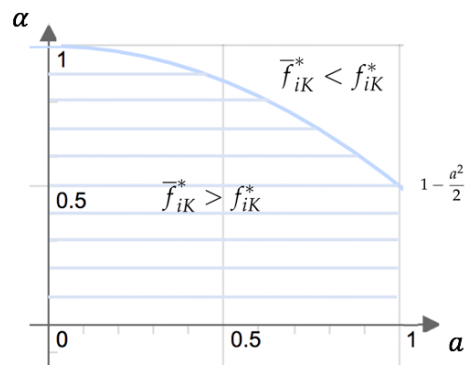
Equilibrium outcomes

In the following section, we compare the commission fees and the prices set with and without MFN clauses.

Proposition 6 *MFN clauses are detrimental to consumers if platforms have most of the market power, however, they lead to lower prices and higher consumer surplus when $\alpha > 1 - \frac{a^2}{2}$ (i.e. hotels have the bargaining power and the competition between hotels is high).*

Proof. See Appendix A.5 ■

Figure 1: Comparison of equilibrium fees with and without MFN clauses with respect to the competition between hotels (a) and their bargaining power (α) regarding platforms



From Proposition 3 we know that MFN clauses dampen competition between platforms. When platforms have a greater bargaining power than hotels ($\alpha < \frac{1}{2}$), platforms directly benefit from this lower level of competition compared to the no-restriction setting and are able to set higher commission fees whatever the level a of competition between hotels.

Conversely, when hotels have a greater bargaining power than platforms ($\alpha \geq \frac{1}{2}$) commission fees \bar{f}_{iK}^* may be lower than the fees set under no-restriction f_{iK}^* . This comes from the fact that the status-quo profits of hotels may be higher under MFN clauses: $\bar{\pi}_i^{st} \geq \pi_i^{st}$.

Consider the status-quo profit of the hotel i , that is the profit of hotel i when the negotiation between i and K failed. Hotel i will only be displayed on the platform L . Without MFN clauses, i will set p_{iL}^* on the only platform where it is listed, platform L . Under MFN clauses, the hotel has to set the same price on both platforms but as negotiations failed, the hotel i only has one price to set on one platform. MFN clauses do not apply to the hotel i who will set \bar{p}_{iL}^* on platform L only.

As hotels and platforms do not observe the output of the negotiation and have passive beliefs, hotel i set \bar{p}_{iL}^* without being constrained by MFN clauses and anticipating that its competitor the hotel j is still restricted by MFN clauses and has to set the same prices on both platforms. This affect the hotel's status-quo profit compared to the one without restriction as the competition setting between hotels is different. While hotel i has the ability to decrease its price on one platform to attract demand and gain market share, the hotel j has to decrease its price on both platforms if it wants to responds to the price decrease of i . This decrease in price is much more costly to hotel j since it affects its profits on both platforms. Hence, the hotel i benefits from the fact that its competitor is restricted by MFN clauses while it is not, leading to a higher status-quo profit under MFN clauses compared to the benchmark setting: $\bar{\pi}_i^{st} > \pi_i^{st}$.

On the other hand, if negotiation succeed, the structure of the profits of the hotel i with or without MFN clauses are the same: $\pi_i^a = \bar{\pi}_i^a$. Thus, the difference between the profit of hotel i and its status-quo profit under MFN clauses is lower than without restriction: $(\bar{\pi}_i^a - \bar{\pi}_i^{st}) \leq (\pi_i^a - \pi_i^{st})$. As the cost for the hotel i of breaking the negotiations is lower under MFN clauses compared to the non-restriction setting, the hotel i gains bargaining power against the platform K and has the ability to negotiate lower commission fees compared to the benchmark setting without MFN clauses.

In addition, the higher is the competition between hotels (a close to 1), the larger is the demand that the hotel i is able to attract by decreasing its price on platform L while its competitor has to do it on both platforms under MFN clauses and the higher will be the status-quo profit of the hotel: $\bar{\pi}_i^{st}$. Thereby, the bargaining power allowing i to negotiate lower commission fees increases with the level of competition between hotels a .

In conclusion, with $\alpha > \frac{1}{2}$ and a is getting closer to 1, hotels are able to negotiate lower fees and because competition between them is high, this decrease in marginal cost is passed to consumers. In this specific setting, MFN clauses are beneficial to both hotels and consumers.

1.6 Robustness and extensions

Observability of the output of the negotiations

Our model assumes that the outcome (success or not) of the negotiation between the hotel and the platform is not observable. In the following paragraphs we discuss the role of this hypothesis and the consequences if we relax it.

So far we assume that in Stage 2, success or failure of the negotiations is only observable by the hotel and the platform involved in the negotiation. In stage 1, this hypothesis is illustrated by the equation of the status-quo demand functions (2) and (3) where p_{jL}^a, p_{jK}^a are the prices set by the hotel j not knowing that negotiation failed anticipated by the hotel i .

Take the settings without MFN clauses and consider now that the output of the negotiation between hotel i and platform K is observable by other players. The hotel j is now able to observe that only 3 goods will be available to purchase in case of a failure in the negotiation between i and K . Anticipating a change in demand for its hotel in platform K where hotel i is no longer present, its pricing strategy during stage 1 will change, impacting the anticipations of the hotel i .

Lemma 4 *The status-quo price p_{jK}^{st} anticipated by the hotel i , if negotiation between i and K fails and that the output is observable is:*

$$p_{jK}^{st}(f_{iL}^a, f_{jL}^a) = \frac{1}{2} \left(1 + f_{jK} + \frac{a(2(f_{iL} - 1) + a(f_{jL} - 1))b}{4 - a^2} \right)$$

Contrary to the subgame equilibrium price p_{jk}^a anticipated by i if negotiation output is secret, see equation (1), p_{jK}^{st} varies with the parameter b (level of substitution between platforms). p_{jK}^{st} decreases in b , with $b = 0$, the hotel j is in a monopoly position on platform K and set the monopoly price. As b increases, more and more users switch from one platform to another and j adapts his price to the competitive situation.

Lemma 5 *When the outcome of the negotiations is observable, the status-quo prices set by hotel j on platform K (p_{jK}^{st}) in case of a breach of negotiation between i and K is higher than the price anticipated by the hotel i if the output of the negotiation was secret (p_{jk}^a):*

$$p_{jK}^{st} \geq p_{jk}^a \quad (1.8)$$

Proof. See Appendix A.7 ■

This result directly comes from the fact that the hotel j is now able to observe its monopoly position on platform K while negotiation between i and k failed and to adjust its price consequently. Note that the difference between p_{jK}^{st} and p_{jk}^a is decreasing in b . A high level of substitutability between platforms constraints the hotel j in setting a monopoly price on platform K .

Proposition 7 *Fees set by platforms under no restriction are lower when the outputs of the negotiations are observable. We have:*

$$\begin{cases} f_{iK}^{obs} < f_{iK}^{sec} : \text{if } a, b \text{ and } \alpha \in]0, 1[\\ f_{iK}^{obs} = f_{iK}^{sec} : \text{if } a = 0 \text{ or } \alpha = 1 \text{ or } b = 1 \end{cases}$$

Proof. See Appendix A.7 ■

Consider the negotiation between i and K . If negotiations fail, we know from Lemma 5 that the status-quo equilibrium price (p_{jK}^{st}) of the hotel j on platform K increases compared to the situation where negotiation outputs are secret, while other prices stay the same. Consequently, the demand for hotel j on platform K will decrease, and platform K 's profit will also decrease and be lower than its profit in the setting where output of the negotiation is secret. Thus, platform K has more to lose from a break in the negotiation with the hotel i while the outcome is observable. The hotel has then a stronger bargaining power and negotiate lower fees $f_{iK}^{obs} < f_{iK}^{sec}$.

Note that the difference between f_{iK}^{obs} and f_{iK}^{sec} is decreasing in b and α and increases in a .

Endogenous MFN adoption

In the game described in Section 3.1, we consider that at either no platform or both platform set MFN clauses simultaneously. We do not consider asymmetric situations in which only one of the two platforms adopts MFN clauses.

We now consider that the decision of setting MFN clause is endogenously taken by each platform. 3 cases may occur, no platform set MFN clause, both platforms set MFN clauses and only one platform sets MFN clauses. The two first symmetric situations are respectively computed in Section 4 and Sections 5 of this paper.

Regarding the asymmetric situation where platform K decides to set MFN clauses whereas platform L don't. To be listed on platform K , the hotel i needs to set p_{iK} below or equal to the lowest price available elsewhere. Thereby, hotel i has the choice between setting the 2 same prices on platforms K and L , or setting a price p_{iL} on L that is higher than p_{iK} . Johansen and Verge (2017)[19] show this asymmetric setting is not a pure strategy equilibria.

The intuition is the same than for Proposition 6. If platform K sets MFN clauses and L don't, the hotel i is more tempted to deviate and be only listed on L to not be constrained by MFN clauses. For this reason, platform don't have incentive to adopt MFN clauses unless the rival adopts the clauses as well.

1.7 Conclusion

The main result of this article is that Most Favoured Nation clauses on the on-line booking market are detrimental to consumers if platforms have most of the bargaining power, they dampen competition between platforms, lead to higher commission fees and higher hotel rooms' prices. The stronger is the competition between platforms the higher is their incentive to set MFN clauses. However, MFN clauses lead to lower commission fees and higher consumer surplus when hotels own the bargaining power and competition between them is high.

Our results directly contribute to the growing literature on the competitive effects of MFN clauses on online platforms. We show that the balance of bargaining power between platforms and hotels plays an important role in assessing the impact of MFN clauses on the economy. This article provides a theoretical framework that support the latest decisions made by competition authorities regarding the hotel booking industry where big platforms such as Booking.com allegedly own more bargaining power than individual hotels.

Empirical evidences support our results. Mantovani, Piga and Reggiani (2019)[23] show that prices in the main Mediterranean islands of Italy, France and Spain decrease in 2015 after the antitrust intervention and that the suppression of MFN clauses helped to contain the price surge that was mainly driven by the tourism boom registered in 2016 in the same region. Hunold Kesler Laitenberger Schlutter (2017)[17] show that the suppression of MFN Clauses leads hotel to decrease their prices, in particular on their direct selling channel. And Larrieu (2019)[16] shows that the end of Most Favoured Nation clauses imposed by public authorities to OTAs in Paris causes a decrease of about 3.1% to 4.5% in the average level of hotels' prices. All these findings are consistent with our results showing that while platforms have a strong bargaining power, MFN clauses increase final price and constrain the hotel in its pricing strategy.

In addition, we show that hotels with a high bargaining power may negotiate lower commission fees resulting in lower prices. This result is aligned with the empirical findings of Mantovani et al.(2019) [23] show that hotels affiliated with chains decreased their prices more than independent hotels, both in the short and medium run. This result

The model we developed is tractable and can be extended in many directions. First, we studied the case where only 2 hotels and 2 platforms interact. It may be interesting to generalise the model to n hotels and p platforms to come closer to the reality where thousands of hotels face few major platforms. Second, we only consider MFN clauses on prices in this article. But MFN clauses also apply to the number of rooms that each hotel has to make available on each platform. Besides, capacity constraints are important to consider when one analyses the hotel industry. Thereby, it would be interesting to model quantity competition subject to capacity constraints to analyse the impact of MFN clauses on quantities offered by hotels to each platform.

Finally, this article brings additional elements to the current discussions on MFN Clauses set by online platforms. It clearly shows that the level of bargaining power of the actors needs to be assessed when analyzing the competitive effects of Most Favoured Nation clauses in the context of online booking. In alignment with the current literature, we find that MFN clauses dampen competition between platforms and are detrimental to consumers in the majority of the cases. However, we bring a new result showing that MFN clauses may lead to lower commission fees and lower prices when hotels' bargaining power is high and the competition between them is intense. Before banning or allowing MFN clauses, the difficulty for competition authorities will be to evaluate this level of bargaining power to see if MFN clauses may have a positive impact on a given market.

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1.8 Appendix

Proof of Lemma 1

In stage 2 of the game, the negotiations between hotels and platforms are settled and the hotel i faces a commission fee f_{iK}^* for each room sold through platform K . The hotel i then sets the final price at which its rooms will be offered on platform K (p_{iK}) and platform L (p_{iL}).

From the inverse demand function of the price p_{iK} we derive the following demand function:

$$D_{iK} = \frac{1 - p_{iK} + b(p_{iL} - 1) + a(p_{jK} - 1) + ab(1 - p_{jL})}{(a^2 - 1)(b^2 - 1)}$$

In stage 2, the hotel i knows the outcome of its two negotiations from stage 1 but cannot observe the outcome of the negotiation between the hotel j and the platform K and L .

Assume the four negotiations succeeded in stage 1. Both hotel are present on both platforms. In stage 2, the profit of the hotel i is

$$\pi_i = D_{iK}(p_{iK}, p_{iL}, p_{jK}^a, p_{jL}^a)(p_{iK} - f_{iK}^*) + D_{iL}(p_{iK}, p_{iL}, p_{jK}^a, p_{jL}^a)(p_{iL} - f_{iL}^*)$$

Where f_{iK}^* and f_{iL}^* are the observed outcomes of the hotel i negotiations with platform K and L , and p_{jK}^a and p_{jL}^a the price of the hotel j on platform K and L anticipated by the hotel i .

Assuming correct anticipation, the two best responses final prices of each hotel i are:

$$p_{iK}^{BR}(p_{jK}, f_{iK}) = \frac{1 + f_{iK}^* - a(1 - p_{jK}^a)}{2}$$

Where p_{jK}^a is the anticipated price set by the hotel j on platform K . The intersection of the best responses gives the subgame equilibrium prices denoted p_{iK}^e :

$$p_{iK}^e(f_{iK}^*, f_{jK}^*) = \frac{2(1 + f_{iK}^*) + af_{jK}^* - a(1 + a)}{4 - a^2}$$

Proof of Lemma 2

Consider the stage-2 of the game, where negotiations between hotels and platforms are settle and the four commission fees $\bar{f}_{iK}, \bar{f}_{jK}, \bar{f}_{iL}, \bar{f}_{jL}$, set under MFN clauses are fixed. Assume the four negotiations succeeded in stage 1. Both hotels are present on both platforms and are constrained by the MFN clauses clauses to set the same prices on both platforms.

Under MFN clauses, the demand function for the hotel i on platform K is:

$$\bar{D}_{iK} = \frac{-1 + \bar{p}_{iKL} + a(1 - \bar{p}_{jKL})}{(a^2 - 1)(b + 1)}$$

The profit of the hotel i under MFN clauses is:

$$\bar{\pi}_i = \bar{D}_{iK}(\bar{p}_{iKL}, \bar{p}_{jKL}^a)(\bar{p}_{iKL} - \bar{f}_{iK}^*) + \bar{D}_{iL}(\bar{p}_{iKL}, \bar{p}_{jKL}) (\bar{p}_{iKL} - \bar{f}_{iL}^*)$$

Where \bar{p}_{iKL} stands for the price of rooms set by the hotel i under MFN clauses on platform K and L and \bar{p}_{jKL}^a is the price of j on platform K and L anticipated by i . The best response final price of hotel i is:

$$\bar{p}_{iKL}^{BR} = \frac{2 + \bar{f}_{iK}^* + \bar{f}_{iL}^* + 2a(\bar{p}_{jKL})}{4}$$

The intersection of the best responses give the subgame equilibrium prices denoted:

$$\bar{p}_{iKL}^e(\bar{f}_{iK}^*, \bar{f}_{iL}^*, \bar{f}_{jK}^*, \bar{f}_{jL}^*) = \frac{4 + 2(\bar{f}_{iK}^* + \bar{f}_{iL}^*) + a(\bar{f}_{jK}^* + \bar{f}_{jL}^*) - 2a(1 + a)}{2(4 - a^2)} \quad (1.9)$$

Proof of Proposition 4

Consider now the stage 1 of the game where each hotel will negotiate the level of commission fees he is willing to accept to sell his rooms through the platform. The Nash program of the negotiation between the platform K and the hotel i is the same than before except that the hotel can only set one price, the same on

both platforms:

$$\max_{\bar{f}_{iK}} (\bar{\pi}_i^a - \bar{\pi}_i^{st})^\alpha (\bar{\pi}_K^a - \bar{\pi}_K^{st})^{(1-\alpha)}$$

where $\bar{\pi}_i^a$ (resp. $\bar{\pi}_K^a$) is the anticipated profit of the hotel i (resp. platform K) under MFN clauses and $\bar{\pi}_i^{st}$ (resp. $\bar{\pi}_K^{st}$) is the anticipated status-quo profit under MFN clauses earned by the hotel i (resp. K) if the negotiation breaks, all other negotiations being successful.

Assume a breakdown in negotiating between the hotel i and the platform K . Remember that the outcome of the negotiation is secret, only i and K can observe the output of the negotiation and can anticipate the absence of i on platform K leading to:

$$\bar{D}_{iL}^{st}(\bar{p}_{iL}^{st}, \bar{p}_{jKL}^a) = \frac{1 - \bar{p}_{iL}^{st} - a(1 + \bar{p}_{jKL}^a)}{1 - a^2}$$

$$\bar{D}_{jK}^{st}(\bar{p}_{jKL}^a) = \frac{1 - \bar{p}_{jKL}^a}{1 + b}$$

Where \bar{p}_{jKL}^a is the anticipated price of by the hotel j , under MFN clauses, on both platforms K and L anticipated by the hotel i , and \bar{p}_{iL}^{st} is the status-quo price set by the hotel i on platform K . Note that \bar{p}_{iL}^{st} is no longer constrained by MFN clauses since in status-quo, the hotel i is only present on one platform.

The status-quo equilibrium price of the hotel i is the solutions of the associated Nash program :

$$\max_{p_{iL}^{st}} (\bar{\pi}_i^{st}) = \bar{D}_{iL}^{st}(p_{iL}^{st}, \bar{p}_{jKL}^a) (p_{iL}^{st} - \bar{f}_{iL}^a)$$

Leading to the status-quo price:

$$\bar{p}_{iL}^{st} = \frac{-8(1 + \bar{f}_{iL}^a) - 2a(\bar{f}_{jK}^a + \bar{f}_{jL}^a - 2) + a^2(\bar{f}_{iL}^a - \bar{f}_{iK}^a + 4)}{4(a^2 - 4)}$$

We then derived the subgame equilibrium outcome of the negotiations by

the solving the four Nash programs :

$$\max_{\bar{f}_{iK}} (\bar{\pi}_i^a - \bar{\pi}_i^{st})^\alpha (\bar{\pi}_K^a - \bar{\pi}_K^{st})^{(1-\alpha)}$$

Which leads to a unique symmetric solution:

$$\bar{f}_{iK}^* = \frac{2(a+2)(\alpha-1)(b-1)}{((a-2)a-6)(b-1) - 2\alpha(a^2 - (a+3)b + a - 1)}$$

Proof of Corollary 1

Consider the equilibrium fees under MFN clauses given by Proposition 4:

$$\bar{f}_{iK}^* \equiv \frac{2(a+2)(\alpha-1)(b-1)}{((a-2)a-6)(b-1) - 2\alpha(a^2 - (a+3)b + a - 1)}$$

With $\alpha = 0$, the above equation boils down to

$$\bar{f}_{iK}^* = \frac{-2(a+2)}{(a-2)a-6}$$

Consider now the setting without restriction where platforms are able to collude and still own all the bargaining power ($\alpha = 0$). Let's first compute the equilibrium fees set by these colluding platforms. We know from Lemma 1 and equation (1) that the subgame equilibrium prices set by hotels under no restrictions are:

$$p_{iK}^e(f_{iK}^*, f_{jK}^*) = \frac{2(1 + f_{iK}^*) + af_{jK}^* - a(1 + a)}{4 - a^2}$$

Under collusion, platforms will maximize their joint profit which is:

$$\pi^{col} = (\pi_K - \pi_K^{st}) + (\pi_L - \pi_L^{st})$$

where π_K (resp. π_L) is the profit of the platform K (resp. platform L) under no restrictions and π_K^{st} (resp. π_L^{st}) is the anticipated status-quo profit earned by the platform K (resp. L) if the negotiation breaks, all other negotiations being successful.

Appendix A.3 details the status-quo profits of both platforms with status-quo demands and status-quo prices, allowing us to derive the following maximization program:

$$\max_{f_{iK}^{col}} = (\pi_K - \pi_K^{st}) + (\pi_L - \pi_L^{st})$$

And for $a, b \in [0, 1]$, the fees set by platforms under collusion are:

$$f_{iK}^{col} = \frac{1}{2}$$

It comes that, for $a, b \in [0, 1]$, we have:

$$f_{iK}^{col} < \bar{f}_{iK}^*$$

Commission fees set by platform under MFN clauses are strictly higher than commission platforms would have set under a collusive agreement.

Proof of Proposition 6

From equations (2) we get the fees set without restriction and from equation (5) we get the fees under MFN clauses:

$$f_{iK}^* = -\frac{(a+2)(\alpha-1)(b-1)}{\alpha(a(a+1) - (a+2)b) + a(a+b-1) + 2(b-2)}$$

$$\bar{f}_{iK}^* = \frac{2(a+2)(\alpha-1)(b-1)}{((a-2)a-6)(b-1) - 2\alpha(a^2 - (a+3)b + a-1)}$$

For $a, b, \alpha \in [0, 1]$, the difference between f_{iK}^* and \bar{f}_{iK}^* is equal to zero in 3 cases. For $b = 1$, $\alpha = 1$ and for $\alpha = 1 - \frac{a^2}{2}$.

With $b = 1$, the competition between platforms is perfect and with or without

MFN clauses, at equilibrium platforms set $f_{iK}^* = \bar{f}_{iK}^* = 0$.

With $\alpha = 1$, hotels have all the bargaining power. During negotiations, hotels maximize their profit by imposing zero commission fees to platforms. Thereby, for $\alpha = 1$, we have $f_{iK}^* = \bar{f}_{iK}^* = 0$.

With $\alpha = 1 - \frac{a^2}{2}$, we have:

$$f_{iK}^* = \bar{f}_{iK}^* = -\frac{a^2(b-1)}{a(a^2 - a(b+1) - 2) + 4}$$

Furthermore, for $a, b, \alpha \in [0, 1[$ we have:

$$f_{iK}^* \leq \bar{f}_{iK}^* \equiv \alpha > 1 - \frac{a^2}{2}$$

Meaning that MFN clauses are detrimental to consumers if platforms have the market power and that they lead to lower prices and higher consumer surplus when $\alpha > 1 - \frac{a^2}{2}$ (i.e. hotels have the bargaining power and the competition between hotels is high).

Proof of Lemma 5 and Proposition 7

In this section we assume that the output of the negotiations are observable by all players and that no MFN are set. We derive the equilibrium fees and compare it to the fee set by platforms when the output of the negotiation is secret (Proposition 1)

Stage-2

All players, including the hotel j know the outcome of all negotiations from stage 1. Assume the four negotiations succeeded. Both hotels are present on both platforms. The hotel i sets prices p_{iK} and p_{iL} so as to maximize the following profit:

$$\pi_i = D_{iK}(p_{iK}, p_{iL}, p_{jK}^a, p_{jL}^a)(p_{iK} - f_{iK}^*) + D_{iL}(p_{iK}, p_{iL}, p_{jK}^a, p_{jL}^a)(p_{iL} - f_{iL}^*)$$

where f_{iK}^* and f_{iL}^* are the observed outcomes of hotel i 's negotiations with platforms K and L , and pi_{jK}^a and pi_{jL}^a the price of the hotel j on platforms K and L anticipated by the hotel i .

Nothing changes here compared to the setting where the outputs of the negotiations are secret. It leads to the same subgame equilibrium prices described in Lemma 1.

$$p_{iK}^e(f_{iK}^*, f_{jK}^*) = \frac{2(1 + f_{iK}^*) + af_{jK}^* - a(1 + a)}{4 - a^2} \quad (1.10)$$

The impact of the observability of the output negotiations happens in Stage 1.

Stage-1

To define the status-quo profit, assume that the negotiations between hotel i and platform K breaks. Hotel i is no longer listed on K and 3 goods are for consumers to purchase. As the output of the negotiation is public and observable by all, every players anticipate the changes in demand functions.

Demand functions change to:

$$D_{iL}^{st}(p_{iL}^{st}, p_{jL}^{st}) = \frac{1 - p_{iL}^{st} + a(p_{jL}^{st} - 1)}{1 - a^2}$$

$$D_{jK}^{st}(p_{jK}^{st}, p_{jL}^{st}) = \frac{1 - p_{jK}^{st} + b(p_{jL}^{st} - 1)}{1 - b^2}$$

$$D_{jL}^{st}(p_{jK}^{st}, p_{jL}^{st}, p_{iL}^{st}) = \frac{1 - p_{jL}^{st} + a(p_{iL}^{st} - 1) + b(p_{jK}^{st} - 1)(1 - a^2) - ab^2(p_{iL}^{st} - 1 - a(p_{jL}^{st} - 1))}{(1 - a^2)(1 - b^2)}$$

Where p_{jL}^{st} , p_{jK}^{st} are the status-quo prices set by the hotel j observing the new demand functions with only 3 goods available on the market and p_{iL}^{st} is the status-quo price set by the hotel i on platform L if the negotiation with K failed. All these equilibrium prices are the solutions of the profit maximization program:

$$Max_{p_{iL}}(\pi_i^{st}) = D_{iL}^{st}(p_{iL}^{st}, p_{jL}^{st})(p_{iL} - f_{iL}^a)$$

$$\text{Max}_{p_{jK}, p_{jL}}(\pi_j^{st}) = D_{jK}^{st}(p_{jK}^{st}, p_{jL}^{st})(p_{iL} - f_{iL}^a) + D_{jL}^{st}(p_{jK}^{st}, p_{jL}^{st}, p_{iL}^{st})(p_{iL} - f_{iL}^a)$$

Leading to the status-quo price:

$$p_{iL}^{st}(f_{iL}^a, f_{jL}^a) = \frac{2(f_{iL}^a + 1) + a(f_{jL}^a - a - 1)}{4 - a^2}$$

$$p_{jK}^{st}(f_{iL}^a, f_{jL}^a) = \frac{1}{2} \left(1 + f_{jK} + \frac{a(2(f_{iL} - 1) + a(f_{jL} - 1))b}{4 - a^2} \right)$$

$$p_{jL}^{st}(f_{iL}^a, f_{jL}^a) = \frac{2(f_{jL}^a + 1) + a(f_{iL}^a - a - 1)}{4 - a^2}$$

The status-quo profits anticipated by the negotiating firms are then:

$$\pi_i^{st} = D_{iL}^{st}(p_{iL}^{st}, p_{jL}^{st})(p_{iL}^{st} - f_{iL}^{st})$$

$$\pi_K^{st} = D_{jK}^{st}(p_{jK}^{st}, p_{jL}^{st})f_{jK}$$

The subgame equilibrium outcome of the negotiations is given by the solution of the four Nash programs:

$$\max_{f_{iK}} (\pi_i^a - \pi_i^{st})^\alpha (\pi_K^a - \pi_K^{st})^{(1-\alpha)}$$

In equilibrium, when the output of the negotiation is observable and without MFN restriction, the fees are:

$$f_{iK}^{obs} = \frac{(a-1)(a^2+a-2)(b-1)}{(a(a^2+a-2) - a(a+1))b + a(a+1)((a-2)a+2) + 2(b-2)} \quad (1.11)$$

And by comparing f_{iK}^{obs} with the fees without observability of proposition 1 we show that for:

$$\begin{cases} f_{iK}^{obs} < f_{iK}^{sec}: & \text{if } a, b \text{ and } \alpha \in]0, 1[\\ f_{iK}^{obs} = f_{iK}^{sec}: & \text{if } a = 0 \text{ or } \alpha = 0 \text{ or } a = b = 0 \end{cases}$$

Chapter 2

Pricing strategies in online market places and Price Parity Agreements: evidence from the hotel industry

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Abstract

This paper analyzes how the use of Price Parity Agreements (PPA) has impacted retail pricing strategies of hotels in online market places. We use a unique dataset of prices set by a panel of 863 hotels in Paris that were displayed on more than 25 Online Travel Agencies (OTA) over 3 years. Using a before-after design and controlling for external shocks, we demonstrate that the end of Price Parity Agreements imposed by public authorities to OTAs causes a decrease of about 3.1% to 4.5% in the average level of prices set by hotels. This decrease may be explained by an increase of price discrimination. We show that the level of price discrimination across OTAs increases by 2.3% to 1.4% after the drop of Price Parity Agreements and that the the degree of inter-temporal price discrimination also increases by 3.6% to 2.1%. This paper discusses how these results are related to theoretical foundations.

Keywords: Most Favoured Nation Clause, Price Parity Agreement, Online Booking Platforms, Before-after design, Price Discrimination.

JEL Classification: L13, L41, K21, L86.

2.1 Introduction

Price Parity Agreements, also called Most Favoured Nation clauses, have recently drawn the attention from competition agencies throughout the world. In April 2012, the US department of Justice filed an antitrust lawsuit against HaperCollins, Hachette, Simon & Schuster, Macmillan, Penguin and Apple because they conspired to the end of e-book retailers' freedom competition on retail prices. Publishers were blamed for taking the control on pricing decisions, substantially increasing the prices that consumers paid for e-books. In March 2016, the Supreme Court rejected Apple's final appeal. Apple was thus sentenced to pay \$450 millions to victims. At the same time, the European Commission opened a parallel investigation in December 2011. Publishers and Apple agreed to stop all existing so called agency contracts that provided restrictions on retail prices. In December 2012, the Commission concluded that the commitments were able to restore and preserve competition in the retail prices of digital books.

In spring 2015, the French, Swedish and Italian competition authorities accepted the commitments offered by Booking.com (April 2015[3]) and Expedia Inc. (June 2015), which for a period of five years would remove any Price Parity Agreements restricting price differentials between Online Travel Agencies (OTAs). On August the 6th of 2015, the French Parliament passed a law that banned all agreements placing restrictions on hotel pricing.

From April 2014 (16 months before the end of PPAs) to July 2017 (24 months after the end of PPA), we collected the daily listed prices of a panel of 863 hotels on Kayak.com, Booking.com and Google Hotels. In addition, we collected individual information of each hotel (quality, number of rooms, services...) on TripAdvisor.com. As the removal of PPA affected simultaneously all hotels in France, and several other countries in Europe, we analyze the effects of this removal using a before and after design. The major limitation of this method is the risk of omitted variable bias (see Pearl (2009)[28]). To avoid omitting explanatory factors we use several control variables. We first control for external shocks in demand using public data on the number of effective nights booked in Paris. We also control for the entry of Airbnb as a direct competitor of the hotel industry using the number of search request for "Airbnb Paris" on Google.

This article provides an empirical analysis of the effects of the removal of PPAs on 3 aspects of hotels' pricing strategy: (i) the average level of price, (ii) the price discrimination across platforms and (iii) the inter-temporal price discrimination. We show that the end of PPAs imposed by public authorities to online travel agencies (OTAs) in France leads to a decrease of about 3.1% to 4.5% in the average level of hotels' prices, an increase of about 2.3% to 1.43% of the dispersion of prices across platforms and an increase of about 3.6% to 2.1% in the degree of inter-temporal price discrimination. Thanks to our unique dataset, this paper provides the first empirical study of the impact of the drop of PPAs on the average level of hotels' prices in Paris and contributes to the growing literature analysing the effects of PPAs on prices². Moreover, to the best knowledge of the author, this article is the first to empirically study the impact of PPAs on price discrimination strategies.

The paper proceeds as follows. Section 2.2 reviews the existing theoretical and empirical literature on PPAs and input price discrimination. A definition of Price Parity Agreement is given in section 2.3. Section 2.4 describes the evaluation methods. Section 2.5 presents the dataset we use for our analysis. The effects of PPAs on hotels' pricing strategy are described in section 2.6 and 2.7. Robustness and extensions are discussed on section 2.8 and we keep the section 2.9 for the conclusion.

²See the literature review in Section 2

2.2 Related literature

This paper is directly related to the literature that studies the competitive effects of PPAs on online platforms. Many recent papers have provided theoretical frameworks that help understanding the effect of PPAs. Boik and Corts (2016) [12] demonstrate that PPAs can lead to higher fees, prices and retailers profit. It can also deter the entry of low end firms. Johnson (2017)[20] extends the model of Boik and Corts (2016) and show that imposing price agreement reduces the competition between platform by cutting their incentive to reduce fees. On the other hand, Johansen and Vergé (2017)[19] proved that when one allows each supplier to sell either through a platform or directly to consumers, whether Price Parity Agreements lead to higher or lower commissions depends on the degree of competition between the suppliers. In particular, they find that PPAs may simultaneously lead to higher profits for platforms and suppliers, and increase consumer surplus. Finally, Larrieu (2019)[22] demonstrates that the balance between the bargaining power of hotels and platforms appears as a key parameter in assessing the competitive effects of PPAs. Most of the time PPAs are detrimental to consumers, however they may also be welfare improving when hotels own the bargaining power and competition between them is high.

While the theoretical literature is dense, the empirical literature on PPAs applied to online platform is still nascent. Mantovani et al. (2019)[23] analyze the dynamics of hotel prices listed on Booking.com in the period 2014-16 in the main Mediterranean islands of Italy, France and Spain. They show that prices decreased in 2015, the year in which the major antitrust decisions took place, whereas they bounced back in 2016. Hunold, Kesler, Laitenberger and Schlutter (2017)[17] focus on the direct selling channel of hotels and show that PPA influences the pricing and availability of hotel rooms across online sales channels. In particular, hotels tend to promote the direct online channel more actively at a lower price more often after the ban of PPAs.

This paper is also linked to the literature on input price discrimination. Input price discrimination involves charging different prices to different resellers for the same good. Vulkan (2003)[31] exhibits that e-commerce is specifically prone to price discrimination because of all the data (browsing history, geolocation,...) that allow sellers to analyze price sensitive groups of consumers. Mattioli (2012)[24] shows for instance that the online travel agency, Orbitz, targeted Mac users with costlier prices in comparison to Windows users. By definition, PPAs ban price discrimination between resellers as the resale price decided by hotels should be the same on all platforms. Arya and Mittendorf (2010)[6] analyze the effects of a ban on input price discrimination across resellers in a setting where resellers are asymmetric and one operates in multiple markets. They find that price discrimination leads to price cuts in markets with lower demand and that, when these low demand markets are also less competitive, price discrimination can provide welfare gains by increasing the output on these markets. Miklos-Thal and Shaffer (2018)[25] focus on price discrimination across markets rather than across buyers, and expose that discrimination may have a positive allocation effect: welfare can rise even if total output decreases. Finally, Allain, Chambolle and Turolla (2019)[4] study a reform authorizing wholesale price discrimination that took place in France in 2008. They show that, on average, suppressing the ban on input price discrimination indeed lowered national brand food prices by 3.36% on average compared to the private labels.

2.3 Price Parity Agreements

Price Parity Agreements, also referred as Most Favoured Nation clauses, may refer to different situations depending on the agent who imposes the clauses. The traditional form takes place in a wholesale contract. For example, when a manufacturer asks its retailers not to better promote the brand of a competitor or when a retailer asks its suppliers not to sell its good at a lower price on another sales channels.

On online booking platforms, PPAs refer to agreements between the platform and the hotel that regulates the price and/or supply conditions for the third party, the final consumers, who are not part of the agreements. PPAs are a specific type of agreement that are imposed by platforms to hotels. They are not vertical agreements in the strict sense, because platforms acts as intermediaries, but they have an inherent vertical element. Hotels reservation platforms such as Booking.com, Expedia and HRS incorporated PPAs into their general terms and conditions. Under these conditions, if an hotel wants to be displayed on Booking.com, it has to offer its rooms on this platform at the best prices available on any channel, at the best conditions. If we consider a hypothetical hotel that already offers 10 Queen bedrooms at a rate of 100 euros per rooms, Booking.com or any other platform with PPAs will require to have at least these same conditions of prices and capacities for the same type of rooms.

A distinction has been made by competition authorities between narrow and broad agreements. A narrow agreement between a hotel and an OTA commits the hotel not to charge a lower price on its own distribution channels that the one charged by the OTA to consumers. Under these agreements, the hotel is not able to offer better prices or conditions to someone who makes a reservation offline. The price and conditions between OTA and the direct channels of the hotel have to be the same or better on the OTA. In contrast, a broad (or wide) agreement between a hotel and a OTA commits the hotel not to charge a lower price on competing OTAs. Under these agreements, the hotel has to put the exact same prices and conditions on every booking platform.

2.4 Empirical setting and evaluation methods

In December 2013, in Germany, the Bundeskartellamt prohibited HRS from continuing to apply its prices agreements while at the same time it initiated proceedings against Booking.com and Expedia for applying similar clauses. In both cases, price agreements were suspected of anti-competitive effects. First because they could induce a reduction of competition between the hotel booking website and platforms but also because parity clauses may lead to the foreclosure of smaller platforms or new entrants.

In France, within the scope of a procedure initiated before the Autorité de la concurrence by the main French hotel unions and the Accor group, Booking.com commits to change its commercial practices. Booking.com amended the Price Parity Agreements and removed any clause imposing parity obligations in terms of the availability of rooms or commercial conditions. These commitments were undertaken for 5 years and came into force on the first of July 2015. France, Sweden and Italy worked together, in close coordination with the European Commission, to obtain similar commitments from Booking.com in these three countries. In addition, in August 2015 the Article 133 of the Loi Macron renders null and void all OTA Price Parity Agreements. From this date, platforms such as Booking.com, Expedia, HRS or Oui.Sncf no longer have the right to impose Price Parity Agreements to hotels.

Our objective is to evaluate the causal effect of the ban of PPAs. Program evaluation methods are widely applied in economics to assess the effects of policy interventions and other treatments of interest. Examples include minimum wages and employment policies (Card & Krueger, 1994[14]), health care interventions (Newhouse, 1996[27]), and more recently large-scale online A/B studies in which IP addresses visiting a particular web page are randomly assigned to different designs or contents (see Bakshy et al., 2014[9]). Abadie and Cattaneo (2018)[2] describe the main methodological frameworks of the econometrics of program evaluation and show that randomized experiments and difference in difference are from the most robust tools to perform program evaluation. Unfortunately, as hotels from our panel are all simultaneously affected by the drop of PPAs, we don't have control groups and we cannot use one of these methods.

Thereby, we run a before-after analysis, comparing the change in pricing strategies of hotels before and after the ban of PPAs in France. This evaluation method is simple and powerful but its major limitation is the risk of Omitted Variable Bias (see Pearl (2009)[28]). The tourism industry is very sensitive to external events such as major sport events, political crisis, terrorism etc. During the period of our study (April 2014 to July 2017) many events occurred and may have important effects on hotel pricing strategies. In 2015, Paris suffered from major terror attacks. First in January the 7th (Charlie Hebdo terror attacks) and the second one in November the 13th (6 simultaneous attacks in Paris). On the other hand, in 2016, France was the host of the soccer UEFA European Championship between June the 10th, and July the 10th.

To avoid omitting explanatory factors we use several control variables in addition to market fixed-effects (seasonality, hotel and platform characteristics...). We first control for external shocks in demand using public data on the number of effective nights booked in Paris. We expect the average prices of hotels to be positively correlated with volume of booked nights. We also control for the entry of Airbnb as a direct competitor of the hotel industry. Farronato and Fradkin (2018)[16] demonstrate that Airbnb revolutionized the lodging market by making additional rooms available and especially during peak periods when hotel rooms often sell out and rates skyrocket. This research shows that in the 10 cities with the largest Airbnb market share, including Paris, the entry of Airbnb resulted in 1.3% fewer hotel nights booked and a 1.5% percent loss in hotel revenue. We control for the growth of Airbnb using the number of search requests for "Airbnb Paris" on Google. Here we expect the average price of hotels to be negatively correlated with the increasing notoriety of Airbnb as a direct competitor of hotels in Paris.

2.5 Data

Booking information such as the price of the room, the date of Booking, the type of room or the profile of the customer are highly sensitive data and are considered as industrial secrets by the big players of this industry. We didn't get access to these data so we decided to construct our own data-set.

The backbone of our data are prices of hotel rooms in Paris collected on a daily basis on the meta-search engine Kayak.com between April 2014 to July 2017 for more than 863 hotels on more than 25 platforms. We also collected data on hotels characteristics on TripAdvisor for the same time period. We monitor for specific shocks in hotels' demand using data on the number of effective nights booked in Paris. These data are provided by the French National Institute of Statistics and Economic Studies (INSEE). Finally, we control for the entry of Airbnb as a direct competitor of the hotel industry using the number of search request for "Airbnb Paris" on Google. The following sections describe the collected data.

2.5.1 Kayak data

Kayak is a fare aggregator and travel metasearch engine. From its many services, it provides users a way to compare the price of hotels sold on different platforms. Kayak Software Corporation was acquired by Booking Holdings on May 21, 2013.

We collected data on Kayak.com for 863 hotels in Paris between April, 10th of 2014 to July, 1st of 2017. Data were collected every day from 6am to 8am using a web-scraper robot. We collected 6,097,632 prices offered by hotels in Paris on more than 25 platforms for a twin bedroom for 2 people for 1 night available in 4, 14 and 30 days. For 2 months (June 2014 and September 2015) we also collected data directly from Booking.com, Expedia and Voyage-SNCF to cross-check the prices of room observed on Kayak.com. Results show that less than 4% of prices were significantly different between Kayak.com and Booking.com, Expedia or Voyage-Sncf. Data collected on Kayak are therefore representative of the available online prices for hotel rooms.

Among these 863 hotels, we restricted our panel to the hotels that were displayed on Kayak at least 60% of the time between April 2014 and July 2017, and were present at least once during the 5 first days and the 5 last days of our sample. These restrictions aim at creating a panel that exclude hotels that are closed, changed their name or that decided to no longer be present on Internet during this period. In addition, we decide to exclude from our analyzes hotels of very low quality (zero or 1 star) as it exists very few hotels bellow 1 star in Paris. Finally, these restrictions lead to create a panel of 535 hotels to whom we collected their prices on a daily basis.

For each price that we collected, we observe the date of the search, the date of the stay, the characteristics of the hotel (e.g., description, french quality ranking, brand and sub-brand, location, rating, the number of reviews...) and the name of the platform offering this price. Please note that these observations are listed prices only. We don't know if the rooms were sold at this price or not.

To assess the representativeness of this panel, we compare the category distribution (in term of stars) between our sample and the entire hotel industry in Paris using "ATOOUT FRANCE"³ data. Table 2.5.1 shows that the distribution of hotel categories is almost the same in our sample compared to the existing distribution of all hotels in Paris.

³ATOOUT FRANCE is the France Tourism Development Agency and is responsible for rating hotels from 1 to 5 stars. <https://www.classement.atout-france.fr/>

Table 2.1: Comparison of the distribution of hotels' categories

	Paris	Our Panel
2** hotels	155 (12%)	55 (10%)
3*** hotels	654 (51%)	265 (50%)
4**** hotels	400 (31%)	179 (33%)
5***** hotels	84 (6%)	36 (7%)
Total	1,293	535

2.5.2 TripAdvisor data

TripAdvisor is an American travel and restaurant website company that displays hotel and restaurant descriptions and reviews. Recently, TripAdvisor add the feature of accommodation bookings for users to be able to directly book a restaurant or a hotel room on TripAdvisor's website. TripAdvisor claims to be the largest travel website in the world, with more than 315 million reviewers (active and inactive) and over 500 million reviews of hotels.

We used TripAdvisor to collect descriptive data about our sample of 535 hotels. For each hotel we collected the location of the hotel (longitude & latitude), the TripAdvisor's rating (from 0 to 5), the number of reviews, the size of the hotel (e.g. total number of rooms), the type of hotel (Business, touristic, low budget...) and the services offered by the hotel (e.g. swimming pool, Jacuzzi...).

2.5.3 INSEE data

The National Institute of Statistics and Economic Studies (INSEE) is the national statistics bureau of France. It collects and publishes information about the French economy including the hotel industry. We considered the number of nights sold by all hotels in Paris from April 2014 to July 2017. The INSEE publishes this statistic on a monthly basis.

Figure 2.1: Total number of nights sold by hotels in Paris (source: INSEE)

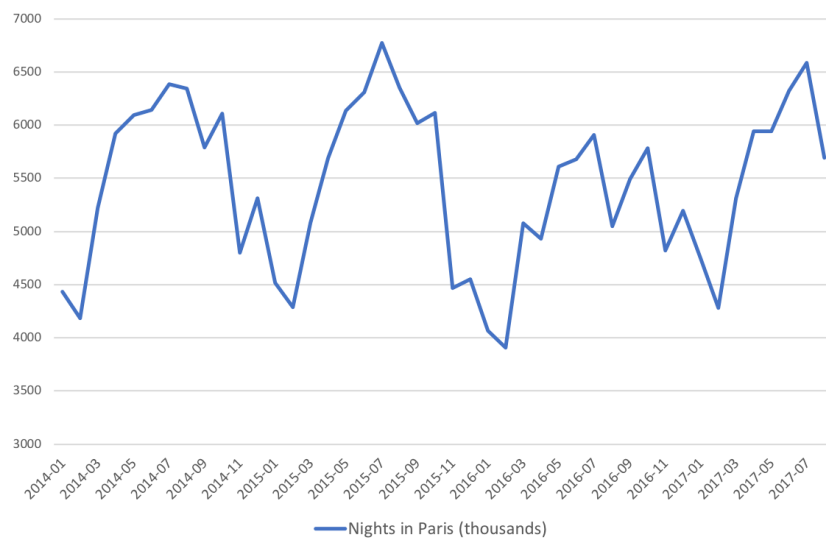


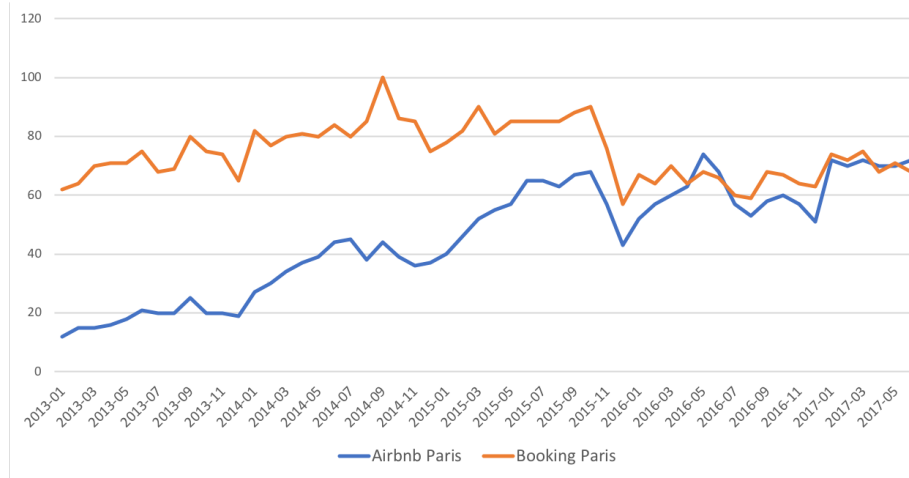
Figure 2.1 displays the total number of nights sold by all hotels in the Paris area. We clearly see that following the Paris attacks in November 2015, the number of sold rooms drops during the following months and is followed by a weak recovery in 2016.

In the next section we describe how we use these data to control for shocks in demands due to external events.

2.5.4 Airbnb

Airbnb is an online marketplace which lets people rent out their properties or spare rooms to guests. It started in October, 2007 under the name of AirBed & Breakfast. Brian Chesky and Joe Gebbia, the two co-founders, came up with the idea of putting an air mattress in their living room and turning it into a bed and breakfast to pay their rent. From its beginning, the site's content had expanded from air beds and shared spaces to a variety of properties including entire homes and apartments, private rooms, castles, boats and other properties. The international expansion of Airbnb started at the end of 2011 and Airbnb opened its office in Paris in Q1 2012.

Figure 2.2: Evolution of "Airbnb Paris" queries on Google compared to "Booking Paris" queries (source: Google Trend)



Since 2012, Airbnb became a strong competitor for the hotel industry and especially in France which is the second country after the US offering the largest number of Airbnb rooms according to Airbnb. To proxy the growing market power of Airbnb we collected monthly number of queries "Airbnb Paris" made on Google between April 2014 and July 2017 and compare them to the amount of queries for hotels in Paris on the top booking platform in France, Booking.com. The following graph shows the evolution of Google queries for "Airbnb Paris" and "Booking Paris".

The Figure 2.2 shows the increase of the Google queries "Airbnb Paris" compared to the queries for "Booking Paris". The drop of December 2015 for both queries is consecutive to the terrorist attacks of November the 13th in Paris.

2.6 Effects of PPAs on the average level of price

The goal of our empirical analysis is to investigate whether the decision of banning PPAs had an impact on the average level of prices set by hotels. Two dates are important landmarks in the banning process of PPAs. First the French Autorité de la Concurrence asked Booking and Expedia to withdraw their PPAs on the 1st of July 2015. Second, on the 6th of August 2015, the Loi Macron banned all PPAs for all OTAS.

According to the Autorité de la Concurrence and the European Commission, PPAs decrease the competition between platforms. Because under PPAs, platforms know that they will be able to offer hotels at the best available price, platforms no longer compete one with each other. Without PPAs, competition authorities are expecting platforms to offer lower commission fees leading to lower hotel room prices. Thus, we are expecting to find a decrease in the average price of hotels after the withdrawal of PPAs.

2.6.1 Specifications

We first estimate the effects of PPAs on the average prices charged by hotel using the following reduced-form specification:

$$\ln(p_{i,j,t,s}) = \beta_0 + \begin{cases} \beta_{1A} PPA_t^A \\ \beta_{1B} PPA_t^B \\ \beta_{1C} PPA_t^C \end{cases} + \sum_{n \in \{i,j,s,d,w\}} \beta_{2n} \lambda_n + \beta_3 Controls_t + \epsilon_{i,j,t,s} \quad (2.1)$$

Where $p_{i,j,t,s}$ is the price charged by hotel i on the platform j for a staying date t booked s days before the staying date. PPA_t is a dummy variable equal to 1 for months after the end of PPAs. The β_{1A} , β_{1B} , β_{1C} coefficients captures the impact of the drop of PPAs on prices in France at 3 different dates :

- Model A: represents the drop of PPA on the 6th August 2015, date of the Loi Macron banning all PPAs for all platforms.

- Model B: represents the drop of PPA on 6th August 2015 with a transition period between the 1st of July 2015 (Autorité de la Concurrence's decision enforcement) and 6th August 2015 (Loi Macron). We therefore compare the average level of prices before the 1st of July 2015 with the prices after 6th August 2015.
- Model C: represents the drop of PPA on 6th August 2015 with a transition period between the 21st of April 2015 (Autorité de la Concurrence's decision press release) and 6th August 2015. We therefore compare the average level of prices before the 21st of April 2015 with the prices after 6th August 2015.

Where $\sum_{n \in \{i,j,s,d,w\}} \lambda_n$ denote all fixed-effects such as:

- The hotel fixed-effect (λ_i) which captures each hotel's characteristics (size, category, offered services, location...)
- The platform fixed-effect (λ_j) which captures the characteristics of the platform selling the room (notoriety, size, marketing investments,...)
- The in-advance booking fixed-effect (λ_s) which captures the effect of booking the same room on the same platform 4, 14 or 30 days in advance.
- The day of the week fixed-effect (λ_d) which captures the seasonality within a week. Demand for hotels is not the same in Paris on Monday, on Wednesday or on Sunday.
- The week of the year fixed-effect λ_w which captures the seasonality of recurrent events that happen every years such as main exhibitions or sport events (Fashion week, Rolland Garos...)

Finally, we include in $Controls_t$, the Airbnb and INSEE data controllers described in the Data section which allow us to control for (1) the competition pressure of Airbnb on hotels, and (2) the monthly seasonality and exceptional events such as the Paris terrorist attacks in November 2015.

In a second time, we add interaction terms between the drop of PPA on the 6th August 2015 and hotel characteristics to look at the impact of the drop of PPA depending on (i) the category of the hotel (number of stars), (ii) the size of the hotel (number of rooms), (iii) the listed hotel's type (e.g. Business Vs. Low Budget) and (iv) whereas the hotel is Independent of belong to a "Brand".

The equation is the following:

$$\ln(p_{i,j,t,s}) = \beta_0 + \left\{ \begin{array}{l} \beta_{1A}(X_i^1 PPA_t^A) \\ \beta_{2A}(X_i^2 PPA_t^A) \\ \beta_{3A}(X_i^3 PPA_t^A) \\ \beta_{4A}(X_i^4 PPA_t^A) \end{array} \right\} + \sum_{n \in \{i,j,s,d,w\}} \beta_{2n} \lambda_n + \beta_3 Controls_t + \epsilon_{i,j,t,s} \quad (2.2)$$

Where are represented the following interaction terms:

- $X_i^1 PPA_t^A$ stands for the interaction terms between the drop of PPAs and the number of stars of the hotel i
- $X_i^2 PPA_t^A$ stands for the interaction terms between the drop of PPAs and the size of the hotel i
- $X_i^3 PPA_t^A$ stands for the interaction terms between the drop of PPAs and the listed category of the hotel i (e.g. Business Vs. Low Budget)
- $X_i^4 PPA_t^A$ stands for the interaction terms between the drop of PPAs and whereas the hotel i is Independent or belong to a "Brand"

2.6.2 Results

In the following section we demonstrate that the end of PPAs on online hotel platforms such as Booking.com, Expedia etc. is associated with an average price decrease of about 3.1% to 4.5% depending on the date at which we consider PPAs to be effectively banned.

Table 2.2: Impact of the drop of PPAs on **the average level of price** for our sample of hotels in Paris

	Model A	Model B	Model C
PPA drop (August 6th 2015)	-0.0456***		
PPA drop (July 1st - August 6th)		-0.031***	
PPA drop (April 21st - August 6th)			-0.036***
Nights Vol.	0.492***	0.4667***	0.480***
AirBnB Vs. Booking	-0.077***	-0.106***	-0.093***
All FE	Yes	Yes	Yes
Observations	2,016,422	2,016,422	2,016,422
Adjusted R^2	0.821	0.821	0.821

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.2 shows that the $\beta_{1A}PPA_t^A$ coefficient representing the drop of PPAs, considering the date of August the 6th 2015 (Loi Macron), is equal to -0.0456 . Thus, a change in $\beta_{1A}PPA_t^A$ parameter leads to a decrease of about 4.5% of the average price $p_{i,j,t,s}$. Model B and C serve as control to see whether the timing of PPA banning has an impact on our result or not. We see that in both cases, the drop of PPA leads to a statistically significant drop in price of 3.1% to 3.6%.

This result is consistent with the existing literature. Boik & Corts (2016)[12] and Johnson (2017)[20] demonstrate that PPAs reduce the competition between platforms, leading to higher commission fees and higher final prices. It is also consistent with the theory of harm developed by the French Autorité de la Concurrence Décision 15-D-06⁴ which states that a drop of PPAs is very likely to increase the competition level between platforms, decreasing the fees charged by platforms to hotels and because the hotel industry is a competitive market, it would decrease the final price paid by consumers.

The coefficient of the *Nights Vol.* and *AirBnB Vs.Booking* control variables are aligned with our expectations. The greater is the demand (higher is *Nights Vol.*) the higher is the average price of hotels' rooms. Regarding hotel alternatives, the stronger is the competition between hotels and alternative offers (illustrated here by AirBnB with the control variable *AirBnB Vs.Booking*) the lower is the price of rooms. This result is aligned with the findings of Farronato and Fradkin (2018)[16] who show that the entry of Airbnb resulted in 1.3% fewer hotel nights booked and a 1.5% percent loss in hotel revenue. In addition, all the fixed-effects described above in 5.1.1 are included in this regression.

The following table shows the results of the specification including the interaction terms between the drop of PPA on the 6th August 2015 and hotel characteristics (see Equation 2).

⁴In french: <http://www.autoritedelaconcurrence.fr/user/avisdec.php?numero=15D06>

Table 2.3: Impact of the drop of PPAs on the average level of price depending of the listed category of each hotel

PPA drop effects on average price				
Business Hotels	-0.0621***			
Family Hotels	-0.0474***			
Luxury Hotels	-0.0350***			
Low Budget Hotels	-0.0530***			
2-Star Hotels	-0.0701***			
3-Star Hotels	-0.0567***			
4-Star Hotels	-0.0372***			
5-Star Hotels	0.00467***			
Less than 33 rooms	-0.0527***			
Between 33 & 43 rooms	-0.0518***			
Between 43 & 61 rooms	-0.0453***			
More than 61 rooms	-0.0273***			
Independent Hotels	-0.0498***			
Brand Hotels	-0.0265***			
All Controls	Yes	Yes	Yes	Yes
All FE	Yes	Yes	Yes	Yes
Observations	1,178,616	2,016,422	2,016,422	2,016,422
Adjusted R^2	0.814	0.821	0.821	0.820

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3 shows that this average decrease of price coming from the drop of PPAs is not evenly distributed between hotels categories. The decrease is higher for Business Hotels (6.21%) and for Low Budget Hotels (5.3%) compare to Luxury hotels. The decrease is stronger on "low quality" hotels (2 and 3-Star hotels), with a decrease from 7.01% for 2-Star hotels to 5.67% for 3-Star hotels⁵. Small hotels (in terms of rooms) are also more impacted with an average decrease of price between 5.27% and 5.18% for hotels with less than 43 rooms. Finally, "Independent Hotels" (neither owned nor linked to a group) face a stronger decrease of their average prices (4.98%) compare to "Brand Hotels"(2.65%).

The fact that small hotels, from a low ranked category and not belonging to a brand are more affected by the decrease of prices coming from the drop of PPAs shows that hotels with a low market power are more affected by the drop of PPAs. This result highlights the findings of Larrieu (2019)[22] who exhibits that the balance of bargaining power between hotels and platforms is a key factor in assessing the effect of the drop of PPAs on prices.

While our results are consistent with the existing literature, we are not able to observe the level of commission fees set by platforms and show that this decrease in the average level of prices is caused by a decrease of fees. Thereby, we explore an additional explanation that may come from the ability of hotels to increase their price discrimination strategy consecutively to the drop of PPAs.

Price discrimination occurs when the same commodity is sold at different prices to different consumers. We demonstrate in the Section 1 that online booking is specifically prone to price discrimination due to the ability of seller to get information about potential buyer and sort customers according to the intensity of their demand. In addition, Möller and Watanabe (2016)[26] show for example that the possibility for competing firms to engage in price discrimination leads to lower prices than under uniform pricing. In the following section we analyze if hotels increase or not their use of price discrimination by looking at two kinds of price discrimination: (i) the Across Platforms Price Discrimination and (ii) the Inter-Temporal Price Discrimination.

⁵Note that the category is listed by TripAdvisor, only about 50% of hotels from our sample have a listed category on TripAdvisor. We restrict the analysis to these hotels, leading to a decrease of observations from 2,016,422 to 1,178,616.

2.7 Effects of PPAs on hotels' price discrimination strategy

According to Amstrong (2006)[5], price discrimination occurs when customers in different market segments are charged with different prices for the same good or service, for reasons unrelated to costs (same marginal cost to produce the goods). It allows firms to extract a bigger part of the consumer surplus by segmenting its offer. Some consumers will pay a higher price than the equilibrium price they should pay and others will now have access to the good at a lower price that fits with their budget constraint.

In this section we explore the impact of the drop of PPAs on the price discrimination strategies of hotels and expect that it allows hotels to increase price discrimination as they now have the ability to target a certain platform at a certain time. Following Clerides (2004)[15] we use the following two price discrimination indices: (i) the Across Platform Price Discrimination for the sale of the same night hotel with the same advance booking:

$$APPD_{i,t,s} = \ln\left(\frac{\max_j p_{i,t,s}}{\min_j p_{i,t,s}}\right)$$

and the Inter-Temporal Price Discrimination for the sale of the same night hotel on a given platform during the booking period (from 30 to 4 days before the staying date):

$$ITPD_{i,j,t} = \ln\left(\frac{\max_s p_{i,j,t}}{\min_s p_{i,j,t}}\right)$$

2.7.1 Across Platforms Price Discrimination

The economical reasons for an hotel to price discriminate across platforms are twofold. It comes first from different "perceived marginal costs" due to differences in the commission rate between platforms ($\frac{c}{1-\theta_j}$). An hotel may prefer to set a lower price on a platform offering a lower commission rate to drive customer on this channel that is less costly for the hotel. In addition, Corts (1998)[7] shows that hotels have asymmetric assessments of consumers demand elasticities across distribution channels, and might adjust their pricing strategies accordingly. Some platforms are specialised in last minute deals with very attractive prices, while others are offering high quality hotels. The difference in willingness to pay of customers between platforms is also explained by geographical and cultural considerations. For example, because a platform attracts mostly US citizens, it will face a higher demand for the 4th of July or Thanksgiving holidays. An hotel may choose to target US customers on these dates by offering targeted prices only on specific platforms.

As Price Parity Agreements doesn't allow hotels to set different prices on different platforms, the drop of PPAs should leads to an increase of price discrimination across platforms. In the following section we analyze the effects of the drop of PPAs on the strategy of the hotel to set different prices on different platforms. Note that almost all platforms had PPAs before the drop ordered by competition authorities but some didn't. this is illustrated by the fact that price discrimination across platform is not equal to zero before the drop of PPAs.

Specifications

We estimate the effects of PPAs on the level of price discrimination across OTAs ($APPD_{i,t,s}$) using the following specification:

$$\ln\left(\frac{p_{i,t,s}^{max_j}}{p_{i,t,s}^{min_j}}\right) = \beta_0 + \left\{ \begin{array}{l} \beta_{1A} PPA_t^A \\ \beta_{1B} PPA_t^B \\ \beta_{1C} PPA_t^C \end{array} \right\} PPA_t + \sum_{n \in \{i,j,k,s,d,w\}} \beta_{2n} \lambda_n + \beta_3 Controls_t + \epsilon_{i,t,s} \quad (2.3)$$

Where $\ln\left(\frac{p_{i,t,s}^{max_j}}{p_{i,t,s}^{min_j}}\right)$ stands for dispersion between the maximum and the minimum of prices for the same hotel i on all platform j for a staying date t booked o days before the staying date.

Where the $\beta_{1A}, \beta_{1B}, \beta_{1C}$ parameters capture the impact of the drop of PPAs on prices in Paris at the same different dates than the previous analysis (1A: August 6th 2015, 1B: July 1st - August 6th and 1C: April 21st - August 6th). Where $\sum_{n \in \{i,j,k,s,d,w\}} \lambda_n$ denotes the same fixed-effects as before (described in section 5.1.1) plus the number of platforms fixed-effect (λ_k). This latter represents the number of platforms on which an hotel i is listed at staying date t booked o days before the staying date to control for the fact that hotels present on a higher number of platforms are more likely to set different prices. And where we include in $Controls_t$ the Airbnb and INSEE data controllers as previously described.

In a second time we analyze the same cross-effects than previously (5.1.1) to analyze the effects of PPAs on the level of price discrimination across OTAs depending on (i) the quality of the hotel (approximated by the number of stars), (ii) the size of the hotel (number of rooms), (iii) the listed category (e.g. Business Vs. Low Budget) and (iv) whereas the hotel is Independent or belong to a "Brand". The equation is the following:

$$\ln\left(\frac{p_{i,t,s}^{max_j}}{p_{i,t,s}^{min_j}}\right) = \beta_0 + \left\{ \begin{array}{l} \beta_{1A}(X_i^1 PPA_t^A) \\ \beta_{2A}(X_i^2 PPA_t^A) \\ \beta_{3A}(X_i^3 PPA_t^A) \\ \beta_{4A}(X_i^4 PPA_t^A) \end{array} \right\} + \sum_{n \in \{i,j,s,d,w\}} \beta_{2n} \lambda_n + \beta_3 Controls_t + \epsilon_{i,t,s} \quad (2.4)$$

The interaction terms matrix is the same than in equation 2.2 and is described in 6.1.1.

Results

We show that the drop of PPAs by OTAs leads to a statistically significant increase of the price discrimination across platforms by hotels in Paris from 2.30% to 1.43% depending of the date at which we consider PPAs to be effectively suppressed. This result is consistent with the findings of EU competition authorities according to which 27% of hotels have started price discrimination across platforms after the end of the PPAs on OTAs⁶.

Table 2.4: Impact of the drop of PPAs on **Price discrimination across platforms**

	Model A	Model B	Model C
PPA drop (August 6th 2015)	0.023***		
PPA drop (July 1st - August 6th)		0.0143***	
PPA drop (April 21st - August 6th)			0.187***
Nights Vol.	-0.112***	-0.104***	-0.110***
Nb. Platform	0.210***	0.210***	0.210***
AirBnB Vs. Booking	-0.003	0.009	0.004
All FE	Yes		
Observations	635,149	635,149	635,149
Adjusted R^2	0.222	0.221	0.221

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

⁶In France and Germany taken together, a higher share of respondents (27%) said that they had price differentiated between OTAs. Paragraph 10, page 7. http://ec.europa.eu/competition/ecn/hotel_monitoring_report_en.pdf

Table 2.4 shows that the drop of PPAs by OTAs leads to an statistically significant increase of the APPD by Hotels in Paris from 2.30% to 1.43%. The coefficient of the *Nights Vol.* is negative (from 11.2% to 10.4%), the greater is the demand (higher is *Nights Vol.*) the fewer are the number of hotels settings different prices on different platforms. The coefficient of the *Nb. Platform* represents the number of platforms on which a specific hotel is listed simultaneously at a specific date. This coefficient, as expected, is statistically significant and positive (21%). The more an hotel is present of different platforms the most likely it will set different prices across platforms. The coefficient of the *AirBnB Vs. Booking* control variable is not statistically significant.

The following table show the results of the specification including the interaction terms between the drop of PPA on the 6th August 2015 and hotel characteristics (see equation 4).

Table 2.5: Impact of the drop of PPAs on **Price discrimination across platforms** depending of the number of stars of each hotel

PPA drop effects on PDAP				
Business Hotels	0.015***			
Family Hotels	0.004*			
Luxury Hotels	0.050***			
Low Budget Hotels	0.015***			
2-Star Hotels	0.001*			
3-Star Hotels	0.017***			
4-Star Hotels	0.038***			
5-Star Hotels	0.034***			
Less than 33 rooms	0.0018***			
Between 33 & 43 rooms	0.032***			
Between 43 & 61 rooms	0.022***			
More than 61 rooms	0.020***			
Independent Hotels	0.0221***			
Brand Hotels	0.030***			
All Controls	Yes	Yes	Yes	Yes
All FE	Yes	Yes	Yes	Yes
Observations	371,930	635,149	635,149	635,149
Adjusted R^2	0.216	0.222	0.222	0.220

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.5 shows that the drop of PPAs leads to a strong increase of the APPD for high quality hotels (4 and 5-Star hotels), an increase of respectively 3.80% for 5-Star Hotels and 3.4% for 4-Star Hotels. Whereas the increase of APPD is only about 1.7% for 3-Star Hotels and close to zero for 2-Star Hotels. Likewise the increase in APPD coming from the drop of PPAs that is much higher for Luxury Hotels (5%) compared to Low Budget (1.5%). These results are aligned with the findings of Koulayev (2009)[21] who shows that Luxury hotels are more responsive to competition in the online channel.

The table also shows that the increase is higher for *Brand Hotels* (3%) compared to *Independent Hotels* (2.21%). Finally, The number of rooms is not a strong driver of the impact of the drop of PPAs on APPD.

2.7.2 Inter-Temporal Price Discrimination

In a second time, we measure the effects of PPA on the capability of firms to engage in inter-temporal price discrimination ($ITPD_{i,j,t}$) within the same sale channel. ITPD is an important pricing strategy closely related to third-degree price discrimination and the fact of segmenting its market into groups which are willing to pay different prices for similar or the same good. In the context of hotel booking it mainly consists in charging different prices at different times for the same hotel room. As hotels rooms are perishable goods that lose all their value when the staying date is passed, hotels use inter-temporal price discrimination to maximize their revenue.

To capture the degree of price discrimination, we use a standard measure of price discrimination from Clerides (2004)[15]: the log of the ratio between the maximum and the minimum prices observed in a booking period for a hotel-night of stay combination.

Note that Inter-Temporal Price Discrimination may be a costly pricing strategy to implement as it needs a continuous adjustment of prices. For that reason one may believe that small hotels are less likely to use such pricing tool. However, Table 8 (in Appendix) shows that if we consider our panel of hotels, Independent and Brand hotels are both using ITPD. Prices of Independent Hotels change by 18.6% and Brand Hotel make their price change by 17.2% between 30 to 4 days prior to the booking date.

Specifications

The estimating specification is the following:

$$\ln\left(\frac{p_{i,j,t}^{max_s}}{p_{i,j,t}^{min_s}}\right) = \beta_0 + \left\{ \begin{array}{l} \beta_{1A} PPA_t^A \\ \beta_{1B} PPA_t^B \\ \beta_{1C} PPA_t^C \end{array} \right\} PPA_t + \sum_{n \in \{i,j,k,d,w\}} \beta_{2n} \lambda_k + \beta_3 Controls_t + \epsilon_{i,j,t} \quad (2.5)$$

Where $\ln\left(\frac{p_{i,j,t}^{max_s}}{p_{i,j,t}^{min_s}}\right)$ stands for difference between the minimum and the maximum price reached by the same hotel i for a staying date t at a booking date going from 30 days to 4 days prior the staying date.

Where $\left\{ \begin{array}{l} \beta_{1A} PPA_t^A \\ \beta_{1B} PPA_t^B \\ \beta_{1C} PPA_t^C \end{array} \right\}$ captures the impact of the drop of PPAs on prices in

Paris at the same different dates than the previous analysis (1A: August 6th 2015, 1B: July 1st - August 6th and 1C: April 21st - August 6th).

Where $\sum_{n \in \{i,j,k,d,w\}} \lambda_n$ denote the same fixed-effects as before (described in section 5.1.1)

As for the previous analysis, we add interaction effects between the drop of PPA on the 6th August 2015 and hotel characteristics depending on (i) the quality of the hotel (approximated by the number of stars), (ii) the size of the hotel (number of rooms), (iii) the listed category (e.g. Business Vs. Low Budget) and (iv) whereas the hotel is Independent or belong to a "Brand". The equation is the following:

$$\ln\left(\frac{p_{i,j,t}^{max_s}}{p_{i,j,t}^{min_s}}\right) = \beta_0 + \left\{ \begin{array}{l} \beta_{1A}(X_i^1 PPA_t^A) \\ \beta_{2A}(X_i^2 PPA_t^A) \\ \beta_{3A}(X_i^3 PPA_t^A) \\ \beta_{4A}(X_i^4 PPA_t^A) \end{array} \right\} + \sum_{n \in \{i,j,d,w\}} \beta_{2n} \lambda_n + \beta_3 Controls_t + \epsilon_{i,j,t} \quad (2.6)$$

The interaction terms matrix is the same than in equation 2.2 and is described in 6.1.1.

Results

We show that the drop of PPAs by OTAs leads to a statistically significant increase of the Inter-temporal Price Discrimination by Hotels in Paris from 3.6% to 2.1%. Without PPAs, hotels change their prices more often when the staying date is approaching. This result is consistent with the fact that PPAs constrain hotels in their pricing strategies. Under PPAs, if the hotel i wants to change its price on a specific platform to attract more customers, it will have to make these changes on all platforms. Without PPAs, the hotel has the ability to limit a specific rebate on a specific platform without impact its sales on other platforms. However, to the knowledge of the author, it exists today no literature that specifically looked at the impact of PPAs or any vertical restraints on the price discrimination strategy of the seller.

Table 2.6: Impact of the drop of PPAs on **Inter-temporal Price Discrimination** by hotels in Paris

	Model A	Model B	Model C
PPA drop (August 6th 2015)	0.036***		
PPA drop (July 1st - August 6th)		0.035***	
PPA drop (April 21st - August 6th)			0.021***
Nights Vol.	0.034***	0.034***	0.063***
Nb. Platform	-0.025***	-0.026***	-0.030***
AirBnB Vs. Booking	-0.063***	-0.061***	-0.046***
All FE	Yes	Yes	Yes
Observations	635,149	612,502	521,587
Adjusted R^2	0.171	0.169	0.170

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows that the drop of PPAs by OTAs leads to an statistically significant increase of the Inter-temporal Price Discrimination by Hotels in Paris from 3.6% to 2.1%. The coefficient of the *Nights Vol.* is positive. The greater is the demand (higher is *Nights Vol.*) the more an hotel will change its price during the 30 days before the staying date.

The coefficient of the *Nb. Platform* is negative. The more an hotel is present on different platforms the less it will change its price during the 30 days before the staying date. This result may be explained by the menu cost concept first introduced by Sheshinski & Weiss (1977). The more numerous are the channels on which the hotel is listed, the higher will be the costs of changing prices on one of several of these channels.

Finally, this increase of the Inter-Temporal Price Discrimination specifically affects small hotels, leading to an increase of about 4.20% to 4.10% for hotels with less than 43 rooms while the increase in ITPD is only about 2.5% for hotels with more than 61 rooms.

Table 2.7: Impact of the drop of PPAs on **Inter-temporal Price Discrimination** by hotels in Paris depending of their number of stars

PPA drop effects on ITPD				
Business Hotels	0.041***			
Family Hotels	0.040***			
Luxury Hotels	0.037***			
Low Budget Hotels	0.028***			
2-Star Hotels	0.041***			
3-Star Hotels	0.033***			
4-Star Hotels	0.037***			
5-Star Hotels	0.042***			
Less than 33 rooms	0.041***			
Between 33 & 43 rooms	0.042***			
Between 43 & 61 rooms	0.035***			
More than 61 rooms	0.025***			
Independent Hotels	0.036***			
Brand Hotels	0.034***			
All Controls	Yes	Yes	Yes	Yes
All FE	Yes	Yes	Yes	Yes
Observations	371,930	635,149	635,149	635,149
Adjusted R^2	0.134	0.148	0.148	0.147

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.8 Robustness and extensions

2.8.1 Impact of Geographical Competition

Location selection and pricing decisions are critical for businesses with uncertain demand, high costs of product reconfiguration, geographic dispersion, and segmented competition (Baum Haveman, 1997[10]). This is especially true in the hotel industry. Bull (1994)[13] shows that location has become a major factor that influences strategy, especially for promotion and pricing strategies.

In the previous sections we don't explicitly control for Geographical Competition for two main reasons. First, because the hotel fixed effect included in every regression allows to capture most of hotels' characteristics, including its competitive environment. And second, as we run a before and after analysis on the same panel of hotels, we expect the changes in competition between hotels to be relatively small between the before and the after PPA period. However, the following paragraphs aim at checking the robustness of this affirmation.

In Appendix A.1 we use the touristic segmentation displayed on TripAdvisor to build 27 geographical clusters. Each cluster corresponds to a touristic area in Paris. Hotels are not evenly distributed between these clusters as they are more hotels in areas such as Champs-Elysees compared to Republique area. This allows us to capture the competitive pressure for each of these clusters, mainly driven by the number of hotels and the touristic interest of the area.

Table 8 shows the list of these 27 clusters and highlights the fact that Parisian hotels in Le Marais or in Opera - Bourse, all other things being equal, are about 100% more expensive than hotels in Bastille - Oberkampf neighbourhood. We then integrate λ_G dummy variables in equation (2.1), (2.3) and (2.5) to control for the geographical competition and assess the impact on our main results. Table 9 shows that by including geographical considerations, none of the coefficient changes dramatically while the Adjusted R^2 is stable or slightly decreases. This confirms that our results are robust and all ready capture, even if partially, geographical competition.

2.9 Conclusion

The main contribution of our paper is to provide an empirical analysis of the effects of the removal of PPAs on hotels' pricing decisions in the region of Paris. We demonstrate that the end of PPAs imposed by public authorities to online travel agencies (OTAs) in France in 2015 leads to a decrease of about 3.1% to 4.5% in the average level of hotels' prices. This result is consistent with the existing literature. Boik & Corts (2016)[12] and Johnson (2017)[20] show that PPAs reduce the competition between platforms, leading to higher commission fees and higher final prices. It is also consistent with the theory of harm developed by the French Autorité de la Concurrence Décision 15-D-06.⁷ In addition, we exhibit that small hotels, from a low ranked category and not belonging to a brand are more affected by the decrease of prices coming from the drop of PPAs.

As we are not able to observe the level of commission fees set by platforms and show that the decrease in the average level of price is caused by a decrease of fees, we decided to explore an additional explanation that may come from the ability of hotels to increase their price discrimination strategy consecutively to the drop of PPAs. We show that this drop leads to a statistically significant increase of the Across Platforms Price Discrimination from 2.30% to 1.43%. This result is consistent with the findings of EU competition authorities according to which 27% of hotels have started price discrimination across platforms after the end of the PPAs on OTAs⁸.

In addition, we demonstrate that the drop of PPAs by OTAs also leads to an increase of the Inter-temporal Price Discrimination by hotels from 3.6% to 2.1%. This result is consistent with the fact that PPAs constrain hotels in their pricing strategies. Under PPAs, if the hotel i wants to change its price on a specific platform to attract more customers, it will have to make these changes on all platforms. Without PPAs, the hotel has the ability to limit a specific rebate on a specific platform without impacting its sales on other platforms.

⁷In french: <http://www.autoritedelaconcurrence.fr/user/avisdec.php?numero=15D06>

⁸In France and Germany taken together, a higher share of respondents (27%) said that they had price differentiated between OTAs. Paragraph 10, page 7. http://ec.europa.eu/competition/ecn/hotel_monitoring_report_en.pdf

As the removal of PPAs affected simultaneously all hotels in France, we analyze the effects of this removal using a before and after specification and control for external shocks in demand and for the entry of competitors such as Airbnb. Even if we believe that our results are robust, some external factors may still interfere with our analysis. For instance, we cannot completely rule out the fact that the average decrease in price of hotels in Paris may still be affected by the 2015 terrorism attacks.

Finally, our paper directly contributes to the literature on PPAs related to online booking platforms by providing an empirical analysis based on a unique dataset of prices set by a panel of 863 Parisian hotels that were displayed on more than 25 Online Travel Agencies (OTA) over 3 years. We show that the drop of PPAs had a real impact on the pricing strategies of hotels in Paris. Our results are aligned with the existing literature and the theory of harm developed by competition authorities.

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2.10 Appendix

2.10.1 Price differences between neighbourhoods

The estimating specification is the following:

$$\ln(p_{i,j,t,o}) = \beta_0 + \sum_{G \in [1,27]} \beta_{2G} \lambda_G + \sum_{n \in \{i,j,o,d,w\}} \beta_{2n} \lambda_n + \beta_3 \text{Controls}_t + \epsilon_{i,j,t,o} \quad (2.7)$$

Where $\sum_{G \in [1,27]} \beta_{2G} \lambda_G$ are all the geographic clusters dummy variables.

And where $\sum_{n \in \{i,j,o,d,w\}} \lambda_n$ denote all fixed-effects such as:

- The hotel fixed-effect (λ_i) which captures each hotel's characteristics (size, category, offered services, location...)
- The platform fixed-effect (λ_j) which captures the characteristics of the platform selling the room (notoriety, size, marketing investments,...)
- The in-advance booking fixed-effect (λ_o) which captures the effect of booking the same room on the same platform 4, 14 or 30 days in advance.
- The day of the week fixed-effect (λ_d) which captures the seasonality within a week. Demand for hotels is not the same in Paris on Monday, on Wednesday or on Sunday.
- The week of the year fixed-effect λ_w which captures the seasonality of recurrent events that happens every years such as main exhibitions or sport events (Fashion week, Rolland Garos...)

Finally, we include in Controls_t , the Airbnb and INSEE data controllers described in the Data section which allow us to control for (i) the competition pressure of Airbnb on hotels, and (ii) the monthly seasonality and exceptional events such as the Paris terrorist attacks in November 2015.

Table 2.8: Price differences between neighbourhoods

	Price difference	Nb. of hotels
Bastille - Oberkampf	Reference	18
Le Marais	+120%	7
Opera - Bourse	+96.7%	72
Tour Eiffel - Invalides	+93.1%	19
Les Halles	+84.1%	3
Champs-Elysees	+74.1%	67
Louvre - Palais Royal	+64.4%	13
Trocadero	+53.8%	12
Quartier Latin	+53.5%	13
Passy	+38.8%	5
Canal Saint-Martin	+37.1%	8
Notre Dame	+35.3%	3
Odeon - St-Michel	+31.6%	6
St-Germain-des-Pres	+23.9%	25
Entrepot	+20.5%	7
Gare du Nord	+17.4%	21
Batignolles - Monceau	+10%	22
Place d'Italie	+0.7%	2
Montparnasse	0%	30
Belleville - Pere Lachaise	-3.4%	1
Gobelins	-9.5%	5
La Villette	-28.4%	2
Bercy - Nation	-29.3%	20
Montmartre	-34.3%	20
Marne-la-vallee	-35.3%	1
Republique	-39%	4

In the following we integrate λ_G dummy variables in equation 2.1, 2.3 and 2.5 to control for the geographical competition and assess the impact on our main results. Results are displayed in the following table.

Table 2.9: Impact of geographical competition

	Average Price	APPD	ITPD
PPA drop (August 6th 2015)	0.034***	0.024***	0.031***
Nights Vol.	-0.112***	-0.108***	0.035***
Nb. Platform	0.488***	0.210***	-0.025***
AirBnB Vs. Booking	-0.069***	0.001	-0.061
All FE + Geo	Yes	Yes	Yes
Observations	2,016,422	635,149	635,149
Adjusted R^2	0.839	0.221	0.169

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.10.2 Inter-Temporal Price Discrimination depending on hotels characteristics

Table 2.10: Inter-Temporal Price Discrimination depending on hotels characteristics

	ITPD (d-30 to d-4)
Business Hotels	21.6%
Family Hotels	17.6%
Luxury Hotels	18.1%
Low Budget Hotels	17%
2-Star Hotels	21.8%
3-Star Hotels	18.9%
4-Star Hotels	17.3%
5-Star Hotels	16.3%
Less than 33 rooms	22.3%
Between 33 & 43 rooms	21.1%
Between 43 & 61 rooms	20.2%
More than 61 rooms	18%
Independent Hotels	18.6%
Brand Hotels	17.2%

Chapter 3

Evaluation des amendes dans les cas de cartel en France

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Abstract

La sanction financière est l'arme la plus utilisée par les autorités de concurrence à travers le monde pour lutter contre la formation de cartels. Cet article s'intéresse au caractère dissuasif et compensatoire des sanctions financières imposées par l'Autorité de la Concurrence en France. Nous analysons une base de données originale qui recense 57 décisions (portant sur 466 entreprises) relatives à des cartels sanctionnés entre 2006 et 2018 par l'Autorité de la Concurrence, ainsi qu'une estimation de l'élasticité-prix de la demande pour 40% des observations. Nous montrons que les propriétés de dissuasion des amendes imposées par l'Autorité de la Concurrence sont sous-optimales. Seules 2% à 18% des sanctions imposées entre 2006 et 2018 sont dissuasives.

Keywords: Cartels, Amendes, Politique de la Concurrence.

JEL Classification: L13, L41, L42.

3.1 Introduction

Prévenir la formation des cartels et faire cesser ceux qui sont actifs est l'un des principaux objectifs de la politique de la concurrence. Bien que certains pays, dont les Etats-Unis, aient adopté des sanctions pénales contre les dirigeants d'entreprises prenant part à des cartels, les sanctions financières restent le principal outil à la disposition des autorités de concurrence pour empêcher la formation de ces cartels et pour assurer la réparation des dommages associés. La fixation des amendes à un niveau adéquat est donc un enjeu majeur de politique de la concurrence. Cependant, les montants des amendes infligées aux entreprises sont l'objet de débats récurrents. D'une manière générale, en politique de la concurrence, les sanctions ont deux objets: assurer d'une part la dissuasion des pratiques anticoncurrentielles, et d'autre part, la réparation des dommages causés à l'économie. Depuis les travaux fondateurs de Becker (1968) et Landes (1983), la théorie économique s'est intéressée à la dissuasion des activités illicites. L'idée centrale développée par Becker est qu'il est primordial de prendre en compte les incitations des contrevenants (dans le cas qui nous intéresse, les entreprises) à participer aux activités illicites (les cartels). Pour s'assurer que l'objectif de dissuasion est satisfait, le montant de l'amende doit être fixé de telle sorte que la perspective de devoir la payer suffise à faire renoncer aux gains apportés par la participation au cartel. La Commission Européenne intègre cet objectif dans ses Penalty Guidelines (2006, Point 4): "Fines should have a sufficiently deterrent effect, not only in order to sanction the undertakings concerned (specific deterrence) but also in order to deter other undertakings from engaging in, or continuing, behaviour that is contrary to Articles 81 and 82 of the EC Treaty (general deterrence)". Le second objectif des sanctions est d'assurer la réparation des dommages causés à l'économie par les pratiques litigieuses. Satisfaire l'objectif de réparation implique donc de mesurer les dommages causés par le cartel et de s'assurer que l'amende atteigne au moins ce montant.

Si les objectifs affichés par les autorités de la concurrence sont clairs, leur application suscite plus d'interrogations, et l'on peut se demander si les amendes fixées par les autorités de la concurrence sont dissuasives et assurent la réparation des dommages causés à l'économie par les cartels. Une littérature économique récente s'interroge ainsi sur le niveau des amendes fixées par les autorités de la concurrence dans les cas de cartels, tant en Europe qu'aux Etats-Unis. A partir de l'étude d'une importante base de données internationale portant sur 1120 cartels, Connor (2010) affirme ainsi que les sanctions financières définies par les lignes directrices des autorités de concurrence sont trop basses et doivent être augmentées. Dans la même veine, Combe et Monnier (2011) se fondent sur l'étude de 64 cas de cartels condamnés par la Commission Européenne pour affirmer que la quasi-totalité des amendes sont trop faibles pour être dissuasives. Allain *et al.* (2015) réfutent cependant le choix du montant de référence de l'amende optimale et proposent une autre méthode de calcul reposant sur une analyse dynamique des cartels au lieu de l'analyse statique retenue dans les deux articles cités. En se fondant sur l'analyse théorique standard de la collusion, Allain *et al.* (2015) considèrent qu'à chaque période, chaque entreprise prenant part à un cartel doit choisir entre rester dans ce cartel ou en sortir, cette décision étant le fruit d'un arbitrage entre le profit que l'entreprise peut réaliser si elle sort du cartel et celui qu'elle peut retirer en restant dans sa situation de cartel pour une période supplémentaire, étant donné la probabilité de détection et le montant de l'amende si le cartel est détecté. En prenant en compte cette dimension dynamique, Allain *et al.* (2015) proposent une méthode de calcul du montant minimum de l'amende qui satisfasse à la fois les objectifs de dissuasion et de compensation, et comparent ce montant théorique aux sanctions financières imposées par la Commission Européenne à 138 entreprises entre 2005 et 2012. Cet article montre qu'en fonction des hypothèses des paramètres prises en compte, de 30% à 70% des amendes décidées par la Commission Européenne sont supérieures ou égales au montant dissuasif. Mais dans l'ensemble, les propriétés dissuasives des amendes imposées par la Commission Européenne apparaissent très hétérogènes. Ces résultats plaident pour une réflexion plus poussée sur la méthode de détermination des amendes.

Cet article s'intéresse aux sanctions financières imposées aux entreprises participant à des cartels par l'Autorité de la Concurrence française. Nous parlons du cadre dynamique développé par Allain *et al.* (2015) pour analyser, pour chacun des membres d'un cartel, le caractère dissuasif et compensatoire des sanctions financières décidées par l'Autorité de la Concurrence française. Pour ce faire, nous avons construit une base de données originale qui recense 57 décisions relatives à des cartels sanctionnés entre 2006 et 2018 par l'Autorité de la Concurrence. Nous observons ainsi les amendes imposées à 466 entreprises. En suivant Buccirosi et Spagnolo (2007), nous déterminons pour chaque entreprise un montant de référence de l'amende, en fonction des ventes annuelles de l'entreprise, de l'élasticité-prix de la demande du secteur, de la marge contre-factuelle (marge qui prévaudrait en l'absence du cartel, étant données les conditions concurrentielles du secteur), et de l'augmentation de prix causée par le cartel. Les deux derniers paramètres sont, par définition, hypothétiques, et nous envisageons plusieurs scénarios offrant un encadrement raisonnable de leurs valeurs. En revanche, nous observons les ventes annuelles de chaque entreprise, et nous construisons une base de données recensant des estimations de l'élasticité-prix de la demande par secteur provenant de la littérature économique. L'appariement de ces bases de données nous donne une estimation de l'élasticité prix de la demande dans 40% des cas de cartels étudiés. A partir de l'étude de ces données, nous montrons que le caractère dissuasif des amendes imposées par l'Autorité de la Concurrence est très faible: selon les scénarios, entre 2% et 18% des amendes imposées entre 2006 et 2018 à des entreprises ayant participé à des cartels sont dissuasives.

L'article est organisé de la façon suivante. La section 3.2 présente les grandes lignes de la méthode adoptée par l'Autorité de la Concurrence pour déterminer le montant des amendes, et discute du montant optimal de l'amende selon des critères économiques. La section 3.3 présente les bases de données que nous avons construites. La section 3.4 présente ensuite nos résultats sur les propriétés dissuasives et compensatoires des amendes imposées par l'Autorité de la Concurrence, et les conclusions sont présentées dans la section 3.5.

3.2 Méthodologie

Dans cette section, nous rappelons brièvement les critères pris en compte par l'Autorité de la Concurrence pour déterminer le montant des amendes, et nous adoptons ensuite une perspective théorique pour discuter du niveau optimal des amendes. Enfin, nous proposons notre définition de l'amende optimale.

3.2.1 Le montant des amendes en pratique

En France, l'Article 464-2 du Code de commerce définit quatre principes fondamentaux pour déterminer le montant des sanctions pécuniaires imposées par l'Autorité de la Concurrence aux entreprises dont les pratiques sont prohibées par le droit de la concurrence: "Les sanctions pécuniaires sont proportionnées à la gravité des faits reprochés, à l'importance du dommage causé à l'économie, à la situation de l'organisme ou de l'entreprise sanctionnée ou du groupe auquel l'entreprise appartient et à l'éventuelle réitération de pratiques prohibées [...]"

Pour déterminer le montant des amendes infligées aux entreprises ayant participé à un cartel, l'Autorité de la Concurrence ne se fonde pas sur une formule précise. L'article 64-2 du Code de commerce prévoit que les sanctions "sont déterminées individuellement pour chaque entreprise ou organisme sanctionné et de façon motivée pour chaque sanction". Pour chaque entreprise condamnée, le montant de base de l'amende s'établit, selon la gravité des pratiques et des dommages à l'économie, comme un pourcentage (généralement entre 3 et 30%) du chiffre d'affaires annuel de l'entreprise.

Ce montant est ensuite multiplié par un coefficient traduisant la durée de l'infraction de manière non-linéaire (1 pour la première année, auquel s'ajoute 0.5 pour chaque année supplémentaire). A ce montant initial sont appliquées des réductions ou des majorations selon les circonstances particulières au cas (infraction répétée, entreprise concentrant l'essentiel de son activité sur ce marché, etc.). Les amendes peuvent ensuite faire l'objet de réductions, voire d'exonération totale, dans le cadre d'une procédure de clémence, lorsqu'une entreprise fournit suffisamment d'éléments pour démanteler un cartel.³ En cas de non-contestation des griefs et d'engagement de l'entreprise, ou dans le cas où la situation financière de l'entreprise est assez précaire pour que l'amende risque de mettre en danger l'entreprise (entreprise défaillante), le montant peut encore être réduit. Enfin, la loi prévoit un plafond maximal de 10 % du chiffre d'affaires mondial de l'entreprise, que la sanction ne peut en aucun cas dépasser.

3.2.2 Niveau optimal de l'amende

L'objectif de dissuasion implique de fixer l'amende de telle sorte que le gain de profit espéré créé par le cartel est inférieur aux pertes espérées liées à la sanction, c'est-à-dire le montant de l'amende multiplié par la probabilité de détection et de condamnation du cartel. Pour une probabilité de détection donnée, on détermine ainsi un montant minimal au-delà duquel toute amende est dissuasive.

³Cette procédure a été introduite en France par la loi sur les Nouvelles Régulations Economiques de 2001. Le premier cas de cartel détecté grâce à une procédure de clémence a été en France le cartel des portes, en 2006, qui a abouti à une amende totale d'un peu plus de 5 millions d'euros, avec immunité totale pour l'entreprise dénonciatrice.

Le second objectif des sanctions est d'assurer la réparation des dommages causés à l'économie par le cartel. En réalité, l'estimation des dommages est complexe et trop coûteuse pour être systématiquement mise en oeuvre par les autorités de la concurrence. En particulier, l'estimation des pertes de surplus infligées aux consommateurs est un exercice complexe qui repose sur une analyse au cas par cas (voir par exemple OXERA, 2009). Nous proposons donc ici une approche de second rang, en exigeant de toute amende qu'elle permette au moins de récupérer la totalité du gain de profit réalisé par l'entreprise condamnée grâce à sa participation au cartel.

Ces deux objectifs déterminent ainsi un niveau minimal au-delà duquel toute amende sera à la fois dissuasive et restitutive. Nous fixons le niveau d'amende optimal à ce seuil. En effet, si une amende trop faible risque de ne satisfaire ni l'objectif de dissuasion, ni celui de réparation des dommages, une amende trop élevée n'est pas non plus efficace, dans la mesure où elle peut engendrer des coûts sociaux et violer le principe de proportionnalité de la justice. D'une part, une amende trop élevée peut pousser des entreprises à la faillite. Wils (2006) met ainsi en garde contre les risques que la faillite ferait porter aux fournisseurs, clients et créiteurs de l'entreprise, ainsi qu'aux employés qui n'ont pas été partie prenante de la mise en oeuvre du cartel. C'est la raison pour laquelle les autorités de la concurrence en Europe et aux Etats-Unis réduisent généralement les amendes lorsqu'elles menacent la viabilité financière des entreprises condamnées.

Ce risque est également pris en compte dans le contrôle des concentrations et fonde l'argument de "failing firms defense". D'autre part, le droit stipule généralement que les sanctions doivent être proportionnées. La pertinence économique de ce principe a été formalisée par la littérature économique sur la "dissuasion marginale" (voir par exemple Stigler, 1970, ou Mookherjee et Png, 92, 94), qui montre que si les contrevenants ont la possibilité de choisir la gravité de l'infraction qu'ils commettent, la proportionnalité des sanctions les incitera à opter pour des infractions moins graves, car le risque est plus élevé pour des infractions plus graves. Enfin, fixer des amendes trop élevées peut rendre toute la procédure moins dissuasive et accroître le coût de la mise en oeuvre de la loi (voir Acemoglu et Jackson, 2017 ou Hay et Shleifer, 1998).

En effet, comme le montre Andreoni (1991) dans un contexte de dissuasion des activités criminelles, si les jurés fondent leur décision de condamner un suspect en mettant en balance les risques d'erreur de type 1 (ne pas condamner un coupable) et de type 2 (condamner un innocent), alors augmenter la sanction augmente le poids des erreurs de type 2 sans réduire celui des erreurs de type 1. Par conséquent, des sanctions plus élevées peuvent réduire la probabilité de condamnation des activités criminelles, ou des pratiques anticoncurrentielles. Dans la suite de l'article, nous définissons donc le montant optimal de l'amende comme le montant minimal qui satisfasse à la fois aux exigences de dissuasion et de réparation.

3.2.3 Détermination de l'amende de référence

Nous reprenons ici la méthode développée par Allain et al. (2015) pour déterminer le montant théorique de l'amende optimale en fonction d'une série de paramètres relativement simples à mesurer. En considérant un modèle d'interactions stratégiques répétées dans la lignée d'Aubert, Rey et Kovacic (2006), Allain et al. (2015) déterminent le montant optimal de l'amende pour chaque entreprise en fonction du surprofit annuel engendré par la participation de cette entreprise au cartel, $\Delta\pi$, de la probabilité α de détection et de condamnation du cartel, et du nombre d'années d'exercice du cartel, n .

Le cadre d'analyse est le suivant.⁴ Sur un marché, des entreprises symétriques envisagent de former un cartel. Elles ont toutes le même taux d'escompte δ . Le jeu considéré est le suivant, il est répété infiniment. A chaque période, la séquence des décisions est la suivante:

⁴Nous choisissons délibérément ce cadre d'analyse simple, qui permet d'obtenir une formule aisément calculable de l'amende optimale. Apporter des modifications au modèle de base engendrerait bien entendu des variations dans la formule de l'amende optimale, mais la formule que nous considérons est indicative et fournit un point de comparaison raisonnable. Pour une discussion sur la robustesse des résultats, voir Allain et al. (2015).

1. Chaque entreprise décide d'abord de communiquer ou pas avec les autres. Pour que le cartel se forme, toutes les entreprises doivent choisir de communiquer à cette étape, indispensable au fonctionnement du cartel. La communication crée l'infraction, et engendre des preuves de l'activité illicite. En l'absence de cartel, chaque entreprise reçoit le profit concurrentiel π .
2. Si un cartel est formé, chaque entreprise choisit soit de coopérer, soit de dévier. A cette période le profit individuel si toutes les entreprises coopèrent est π^M , le profit individuel de déviation est π^D . On suppose $\pi^D \geq \pi^M > \pi$ et on note $\Delta\pi = \pi^M - \pi$.
3. Si un cartel est formé (il y a eu communication de toutes les entreprises), quelles que soient les actions à l'étape 2, le cartel est détecté et condamné avec une probabilité α . Chaque entreprise doit alors payer une amende F . La détection n'est possible qu'à une étape où le cartel est actif.

Les "trigger strategies" classiques⁵ ne permettent pas de soutenir la collusion si l'amende est suffisamment forte, ce que traduit la condition suivante:

$$F \geq \frac{\pi^M - \pi^D + \delta(1 - \alpha)(\pi^D - \pi)}{\alpha\delta(1 - \alpha)} \quad (3.1)$$

Pour simplifier l'analyse, on adopte des hypothèses "prudentes" en exigeant que l'amende soit suffisante pour dissuader la collusion dans des cas où elle est particulièrement stable, en particulier si les entreprises sont infiniment patientes ($\delta = 1$) et si la déviation du cartel n'est pas profitable ($\pi^D \equiv \pi^M$). Dans ce cas, une condition suffisante pour qu'une amende soit dissuasive est

$$F \geq DF$$

⁵Nous considérons en fait une variante dans laquelle, à la première étape, si une entreprise au moins ne communique pas, toutes les entreprises adoptent par la suite la stratégie concurrentielle; si toutes les entreprises ont communiqué, chacune coopère tant qu'aucune entreprise n'a dévié, une déviation à un moment entraîne le choix de la déviation par tous les autres joueurs pour toutes les étapes suivantes.

où l'on définit l'amende dissuasive minimale DF comme:

$$DF = \frac{\Delta\pi}{\alpha}.$$

De même, l'amende compensatoire minimale, CF , est:

$$CF = n\Delta\pi.$$

En adaptant ensuite le modèle de Buccirosi and Spagnolo (2007) pour calculer les gains des entreprises dans les différentes situations, on peut exprimer ces deux seuils de référence en fonction des paramètres suivants:

- les ventes annuelles de l'entreprise, S ;
- l'élasticité-prix de la demande ε ;
- la marge contrefactuelle, m , c'est-à-dire la marge qui aurait été pratiquée par l'entreprise en l'absence de cartel (cette marge est impossible à observer, mais on peut en donner une approximation qui tienne compte de l'environnement concurrentiel du marché);
- l'augmentation du prix causée par le cartel, k .

L'amende dissuasive minimale DF s'écrit alors:

$$DF = k \frac{((1+m)(1-\varepsilon k) - \varepsilon m)}{\alpha(1+m)(1+k)(1-\varepsilon k)} S \quad (3.2)$$

et l'amende compensatoire minimale, CF , est:

$$CF = nk \frac{((1+m)(1-\varepsilon k) - \varepsilon m)}{(1+m)(1+k)(1-\varepsilon k)} S \quad (3.3)$$

On notera que le modèle implique des restrictions sur l'espace des paramètres: le cartel est profitable si et seulement si $(1 + m)(1 - \varepsilon k) - \varepsilon m \geq 0$. Pour des valeurs de l'élasticité entre 0 et 1, il suffit que l'augmentation des prix due au cartel soit raisonnable ($k < 0.50$), mais pour des valeurs plus élevées de l'élasticité prix, ces contraintes impliquent une borne maximale sur k .⁶ Dans la suite de l'analyse, on se limitera à des couples de valeurs de (m, k) qui satisfont ces contraintes, en particulier, nous supposons $m < 20\%$ et $k < 30\%$.

Dans la suite de l'article, nous calculons ces deux seuils pour chaque entreprise condamnée par l'Autorité de la Concurrence entre 2006 et 2018 dans le cadre d'un cartel. Nous les comparons ensuite aux amendes effectivement imposées afin d'estimer leurs propriétés en terme de dissuasion et de réparation des dommages.

3.3 Les données

Cette section décrit la construction de notre base de données et présente ensuite des statistiques descriptives sur les observations.

3.3.1 Construction de la base de données

La première partie de la base recense 57 décisions relatives à des cartels publiées entre 2006 et 2018 conduisant l'Autorité de la Concurrence à infliger des amendes à 466 entreprises pour un montant total de plus de 4 milliards d'euros (voir Tableau 3.9 en annexe). La base de données contient, pour chaque entreprise sanctionnée, les informations suivantes:

- des informations relatives à la décision (index du rapport, année);
- des informations relatives au marché concerné, notamment, des informations qualitatives sur la demande, l'intensité de la concurrence et l'élasticité de la demande par rapport au prix;

⁶Si ε est grand, et en particulier proche de 2, il faut que $k < \frac{1-m}{2(1+m)}$: pour $m = 10\%$ on doit avoir $k \leq 40\%$, pour $m = 20\%$ on doit avoir $k \leq 33\%$, pour $m = 30\%$ on doit avoir $k \leq 27\%$, et pour $m = 40\%$ on doit avoir $k \leq 21\%$.

- des informations relatives au nombre d'entreprises participantes et à la durée du cartel;
- des informations détaillées sur le montant des amendes par entreprise, à différents stades : l'amende initiale, l'amende modifiée en tenant compte des circonstances particulières (infraction réitérée, essentiel de l'activité sur le marché considéré...), le montant revu après application des programmes de clémence et de coopération, puis l'amende révisée selon la non-contestation de la décision et les engagements pris par les entreprises; enfin, les éventuelles réductions liées aux capacités de paiement des entreprises, notamment en raison de la règle selon laquelle une amende ne doit pas dépasser un certain pourcentage (5% jusqu'en 2010, et 10% depuis) du chiffre d'affaires mondial de l'entreprise mère concernée, et enfin, l'amende finale;
- des informations sur chaque entreprise : son chiffre d'affaires sur le marché concerné, le chiffre d'affaires de l'entreprise mère au niveau mondial;
- le cas échéant, des informations sur les marges réalisées grâce au cartel.

La deuxième partie des données concerne les élasticité-prix de la demande. L'élasticité est un paramètre important de notre analyse car la formule de l'amende optimale en dépend, or elle n'est que rarement renseignée dans les décisions de l'Autorité de la Concurrence. Afin de compléter notre base de données et d'affiner notre étude, nous avons construit une base d'estimations des élasticité-prix de la demande par secteur d'activité. Les données ont été collectées dans des publications scientifiques ou administratives.

Le tableau 3.1 ci-dessous présente les valeurs collectées. Ces estimations de l'élasticité-prix de la demande sont faites au niveau de la catégorie de produits étudiée, ou du secteur – il est à noter que les élasticités varient généralement d'une marque à une autre au sein d'une catégorie de produits, l'élasticité de la demande au niveau d'un produit individuel pouvant donc être supérieure à l'élasticité mesurée au niveau de la catégorie de produits. L'effet de la concurrence entre 2 marques données pour un même produit est par ailleurs capturé par le paramètre k . Nous disposons ainsi d'une estimation de l'élasticité-prix de la demande dans le secteur d'activité de plus de 40% de nos 466 entreprises.

Table 3.1: Elasticité-prix de la demande par secteur

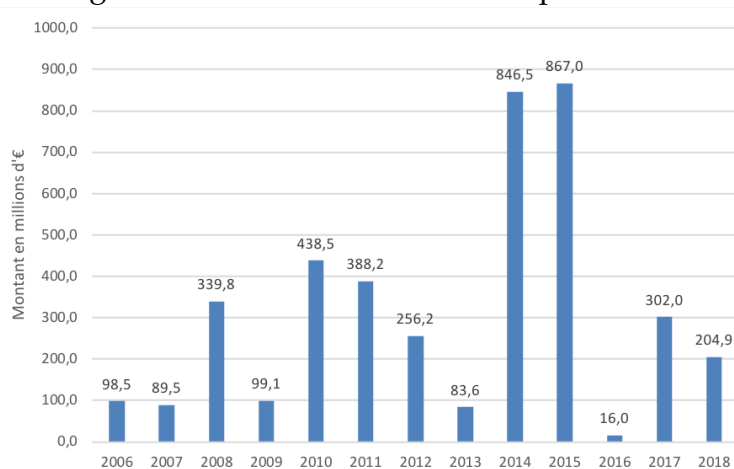
Ref. Décision	Secteur d'activité	Elasticité-prix	Source
06-D-04	Parfumerie	Très faible (0,25)	Cour d'Appel de Paris
06-D-30	Taxi	0,22	Taylor & Greenlaw (2010)
07-D-08	Ciment	Faible (0,5)	ADLC
08-D-13	Nettoyage	0	ADLC
08-D-23	Taxi	0,22	Taylor & Greenlaw (2010)
08-D-33	Autocar	1,46	Laferriere (1992)
09-D-03	Autocar	1,46	Laferriere (1992)
10-D-28	Check cashing - CEIC	0	ADLC
11-D-17	Washing Powder	Faible (0,5)	ADLC
12-D-08	Endives	0,58	Andreyeva et al. (2010)
15-D-03	Yaourts	0,65	Andreyeva et al. (2010)
15-D-04	Boulangerie artisanale	0,43	Pomboza & Mbaga (2007)
15-D-08	Viande de volaille	1,2	ADLC
15-D-19	Transports terrestres	Très faible (0,25)	ADLC
16-D-02	Transports terrestres	Faible (0,5)	ADLC
16-D-09	Armatures métalliques	Faible (0,5)	ADLC
16-D-17	Chauffage mobiles	Elevée (1,75)	ADLC
16-D-20	Modelling	Faible (0,5)	ADLC
18-D-24	Produits électroménagers	Faible (0,5)	ADLC

3.3.2 Statistiques descriptives

Les praticiens s'accordent à noter que le montant des amendes imposées par la Commission Européenne dans les cas de cartels a fortement augmenté dans les années 2000, et notamment depuis les nouvelles lignes directrices de la Commission Européenne de 2006 (voir par exemple Connor, 2011, Veljanovski, 2010, ou Combe et Monnier, 2012). Le graphique 3.1 ci-dessous représente le montant total des sanctions prononcées par l'Autorité de la Concurrence française chaque année sur la période considérée. Entre 2006 et 2018, l'Autorité de la Concurrence a infligé plus de 4 milliards d'euros d'amendes à 466 entreprises pour leurs participations à des cartels. Au vu de l'évolution des montants annuels, il semble en effet que le montant total des amendes s'alourdisse au fil du temps. A première vue, il est possible que les amendes infligées par l'Autorité de la Concurrence en France suivent une évolution comparable à celles de la Commission Européenne. Cependant il est difficile de savoir si cette évolution traduit un durcissement général de la politique de sanctions, ou si elle reflète simplement quelques cas particuliers.

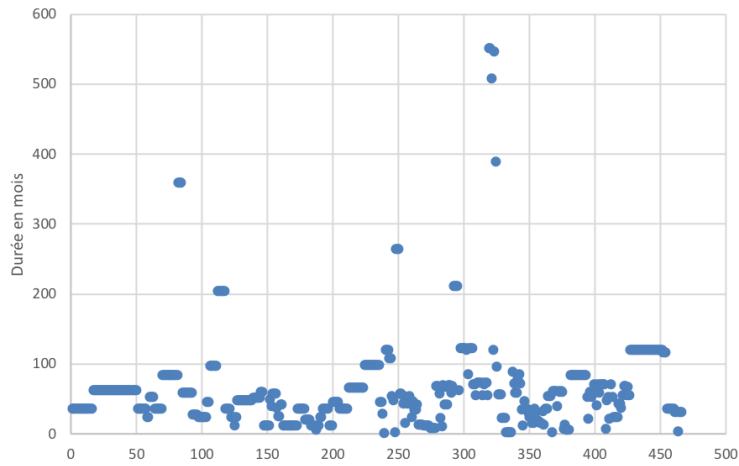
Les années 2014 et 2015 regroupent à elles deux 43% du montant de ces amendes. Quelques cartels en particulier ont été sanctionnés par de fortes amendes pendant ces deux ans. D'une part, le 18 décembre 2014, l'Autorité de la Concurrence a condamné à un total de 841 millions d'euros d'amendes un ensemble de fabricants de produits d'hygiène et d'entretien, pour avoir coordonné leur politique commerciale auprès de la grande distribution, et en particulier pour s'être concertées sur les hausses de prix. Ces pratiques mises en oeuvre entre 2003 et 2006 concernaient le secteur des produits d'entretien et des insecticides, ainsi que le secteur des produits d'hygiène et de soins pour le corps (voir Décision n. 14-D-19 du 18 décembre 2014). D'autre part, le 15 décembre 2015, l'Autorité de la Concurrence a sanctionné 20 entreprises du secteur de la messagerie (transport de colis) pour concertations répétées entre concurrents sur les hausses tarifaires annuelles. Les sanctions financières totales se sont élevées à plus de 660 millions d'euros (voir Décision n. 15-D-19 du 18 décembre 2014).

Figure 3.1: Montant des amendes par année



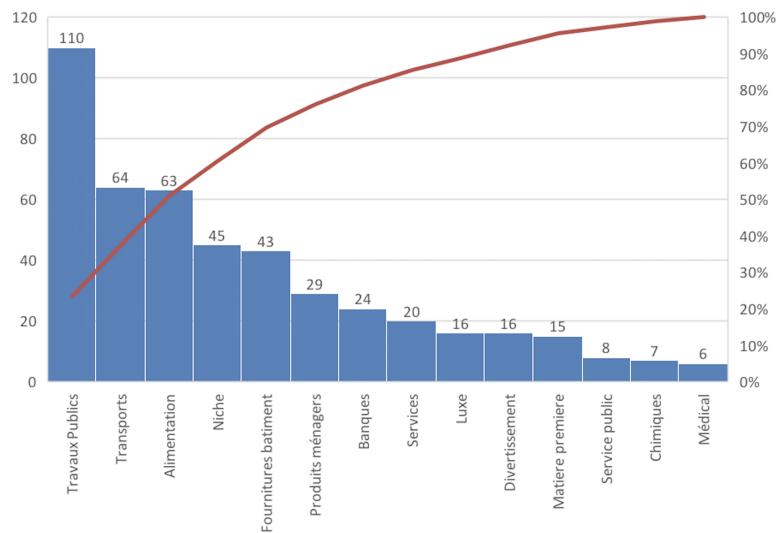
Comme nous l'avons vu dans la section précédente, le calcul de l'amende compensatoire dépend également de la durée du cartel. Cette donnée est cruciale pour notre analyse et c'est pour cette raison que nous avons conservé dans notre base de données uniquement les observations pour lesquelles cette information était disponible. La durée moyenne des cartels détectés par l'Autorité de la Concurrence entre 2006 et 2018 est d'environ 65 mois, soit 5 ans et 5 mois. Le Graphique 3.2 ci-dessous montre la répartition de la durée moyenne du cartel pour les 466 observations de notre base. On voit que dans une majorité des cas, les pratiques incriminées durent moins de 100 mois, mais certains cartels concernés ont duré pendant des périodes très longues (jusqu'à plus de 550 mois).

Figure 3.2: Durée des cartels en mois



Enfin, le Graphique 3.3 ci-dessous montre la répartition des entreprises sanctionnées par secteur d'activité. Plus de 50% des entreprises sanctionnées entre 2006 et 2018 appartiennent aux secteurs des travaux publics, des transports ou de l'agroalimentaire.

Figure 3.3: Répartition des entreprises par secteurs



La section suivante est consacrée à une analyse plus fine du montant des amendes imposées par l'Autorité de la Concurrence.

3.3.3 Analyse du montant initial et final des amendes

Dans cette section, nous proposons d'identifier quelles variables expliquent les montants des amendes observées. Pour ce faire, nous régressons les montants initiaux A_i^I et finaux A_i^F des amendes sur les variables susceptibles d'affecter leur montant. Nous partons de la spécification suivante :

$$\begin{bmatrix} \ln(A_i^I) \\ \ln(A_i^F) \end{bmatrix} = \beta_0 + \beta_1 X_{2012} + \beta_{2,i} \begin{Bmatrix} X_i^{CA} \\ X_i^T \\ X_i^N \\ X_i^E \end{Bmatrix} + \beta_{3,i} X_i^{Cl} + \beta_{4,i} \lambda_i + \epsilon_i. \quad (3.4)$$

Dans l'équation 3.4, $\ln(A_i^I)$ et $\ln(A_i^F)$ représentent les variables expliquées, respectivement le logarithme du montant initial et final de l'amende infligée à l'entreprise i . En nous fondant sur l'analyse descriptive menée à la section 3.3.2, qui a mis en évidence une augmentation importante du montant total des amendes et du montant moyen des amendes par entreprise après 2012, nous introduisons une variable binaire qui caractérise les années postérieures à 2012: X_{2012} vaut 1 si l'amende a été imposée après le 1er janvier 2012 et 0 sinon. Les variables X^{CA} , X^T , X^N et X_i^E sont des variables explicatives issues de l'analyse théorique du montant optimal des amendes menée dans la section 3.2.3: X^{CA} représente le logarithme du chiffre d'affaire annuel de l'entreprise i ; X^T représente le logarithme de la durée de participation de l'entreprise au cartel en mois; X^N représente le logarithme du nombre d'entreprises ayant participées au cartel; enfin, X_i^E représente l'élasticité-prix de la demande des produits vendus par i . Pour finir, X_i^{Cl} vaut 1 si l'entreprise a bénéficié d'un programme de clémence et λ_i indique le secteur d'activité dans lequel se déroule le cartel parmi les 14 secteurs listés dans le graphique 3.

Le tableau 3.2 présente les résultats de cette régression.

Table 3.2: Régression du montant de l'amende

	Amende Initiale	Amende Finale
Après 01/2012	1,590***	1,555***
Chiffre d'affaire	0,936***	0,957***
Durée	0,391***	0,450***
Nb. Entreprises	0.017	-0.009
Elasticité	-0,064	-0,212*
Clémence	1.722**	1.563***
Secteur d'activité	Oui	Oui
Observations	466	466
Adjusted R^2	0.791	0.793

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Le tableau 3.2 confirme tout d'abord l'augmentation importante du montant des amendes après le début de l'année 2012. Le coefficient β_1 compris entre 1,59 et 1,555 signifie que les amendes imposées par l'Autorité de la Concurrence ont été 4,9⁷ fois plus élevées après le 1er janvier 2012. Pour confirmer ce résultat nous avons procédé à un test de sensibilité en modifiant la date de janvier 2012 à janvier 2010, 2011 et 2013. Les résultats présentés en annexe dans le tableau 3.19 montrent que la date du 1er janvier 2012 est celle disposant du pouvoir explicatif le plus important.

⁷ $\exp(1,59) = 4,903$.

Par ailleurs, ce tableau confirme l'importance de la valeur du chiffre d'affaire dans le calcul du montant de l'amende. Avec un coefficient $\beta_{2,i}X_i^{CA}$ compris entre 0,936 et 0,957, une augmentation de 1 millions d'euro du montant de l'amende est expliquée en moyenne par un chiffre d'affaire 2,55⁸ fois plus élevé. De même, l'effet de la durée du cartel dans le calcul du montant de l'amende capté par $\beta_{2,i}X_i^T$ est également positif et significatif. En revanche, alors que l'élasticité-prix de la demande est mise en avant dans les lignes directrices de l'Autorité de la Concurrence, cette dernière ne semble pas significativement expliquer le montant des amendes que nous observons.

Enfin, il est intéressant de remarquer que l'effet des programmes de clémence est positif et significatif. Cela peut s'expliquer par le fait que les entreprises ayant recours à ces programmes sont généralement les entreprises ayant le plus grand risque de faire face à des montants de sanctions élevés. De plus, les entreprises demandant un programme de clémence doivent apporter le maximum de preuves du cartel, ce qui facilite le travail de l'Autorité de la Concurrence et peut expliquer un montant de sanctions avant clémence plus élevé.

Le tableau 3.18 en annexes décrit la valeur des paramètres $\beta_{4,i}$ concernant l'impact du secteur d'activité des entreprises prenant part au cartel sur le montant des amendes reçues par ces entreprises. Certains secteurs se détachent et font apparaître un effet significatif sur le montant des amendes: les secteurs de la chimie et des produits ménagers ont ainsi un effet positif très significatif sur le montant des amendes. Cet effet semble en grande partie expliqué par l'influence de cas particuliers: ainsi, le cas des produits d'entretien, d'hygiène et de soins condamné en 2014 (voir la décision 14-D-19), dans lequel l'ensemble des entreprises a été sanctionné d'une amende totale de 841 Millions d'euros; ou le cas des lessives en 2011 (décision 11-D-17) pour lequel l'amende totale infligée à trois entreprises atteignait 368 millions d'euros.

Dans la section suivante nous analysons le caractère dissuasif et compensatoire des amendes de notre base de données.

⁸ $\exp(0,936) = 2,549$.

3.4 Resultats

Dans cette section, nous calculons dans un premier temps, pour chacune des 466 entreprises de notre base de données, les seuils d'amende dissuasive (DF) et compensatoire (CF). Pour ce faire, nous calculons les montants individuels des seuils définis dans les équations (3.2) et (3.3) présentées dans la section 3.2.3. Nous comparons ensuite ces seuils théoriques aux montants effectifs des amendes reçues par ces entreprises, pour estimer les propriétés dissuasives et compensatoires des sanctions infligées par l'Autorité de la Concurrence.

Dans ce qui suit, nous choisissons comme point de comparaison le montant de base de la sanction (avant les réductions ou les augmentations liées aux programmes de clémence et coopération, à la non-contestation des griefs, ou à la situation financière de l'entreprise): ce montant est déterminé par l'Autorité "eu égard à la gravité des faits et à l'importance du dommage causé à l'économie par les pratiques en cause". A priori, l'amende de base devrait donc refléter au mieux les objectifs de dissuasion et de compensation de l'Autorité, les réductions ou les augmentations qui viennent ensuite moduler le montant de l'amende traduisant des circonstances particulières. Nous menons toutefois des tests de robustesse en prenant comme point de comparaison le montant final de l'amende.

Nous exposons dans un premier temps les hypothèses retenues concernant les valeurs des paramètres de l'analyse (section 3.4.1). Nous présentons ensuite l'analyse des propriétés dissuasives des amendes dans la section 3.4.2, avant de discuter dans la section 3.3.3 la robustesse des résultats à des changements de spécification.

3.4.1 Hypothèses sur les valeurs de paramètres

3.4.1.1 La probabilité de détection α

La probabilité de détection d'un cartel est un paramètre par nature difficile à estimer, car il est impossible de réellement connaître le nombre de cartels qui sont actifs et non détectés. L'OCDE⁹ note ainsi que la probabilité de détection d'un cartel est très probablement de l'ordre d'une chance sur six, voire une chance sur trois: "Some believe that as few as one in six or seven cartels are detected and prosecuted, implying a multiple of at least six. A multiple of three is more commonly cited, however." Cette hypothèse rejoint les estimations de Bryant et Eckart (1991), sur les travaux desquels nous nous reposerons dans la suite de notre analyse. Ces derniers ont estimé la probabilité annuelle de détection d'un cartel à partir de données provenant du Département de la Justice des Etats-Unis entre 1961 et 1988. Leur analyse repose sur un modèle statistique qui décrit le processus de début et de fin d'un cartel à partir d'une chaîne de Markov en temps continu. Ce modèle fournit un nombre théorique de cartel en activité, que les auteurs comparent au nombre réel de cartels détectés par le Département de la Justice pour estimer une probabilité de détection. Bryant et Eckart concluent que la probabilité qu'un cartel soit découvert au cours d'une année est comprise entre 13% et 17%.

Prenant appui sur cette littérature, nous ferons l'hypothèse d'une probabilité de détection du cartel (α) de 15%.¹⁰

⁹Voir OCDE 2002.

¹⁰Cette hypothèse est également retenue par Combe et Monnier (2011).

3.4.1.2 L'augmentation du prix causée par le cartel k

Estimer l'augmentation du prix causée par le cartel est crucial pour déterminer l'impact économique du cartel. Il est cependant difficile d'estimer ce paramètre qui repose sur une analyse contrefactuelle du niveau de concurrence entre entreprises en l'absence de cartel. En effet, même si le niveau de concurrence dans le secteur avant la mise en place du cartel peut être observé, rien n'indique que ce même niveau aurait perduré pendant la période d'existence du cartel si le cartel n'avait pas existé. Par ailleurs, les décisions de l'Autorité de la Concurrence ne fournissent généralement aucune information sur ce point.

La littérature économique offre un certain nombre d'estimations dont les résultats varient généralement entre 5% et 40%. L'OCDE (2003) estime les hausses de prix entre 15 et 20% sur un échantillon de 12 cartels. Connor (2006) utilise une vaste base de données recensant plus de 1100 cartels condamnés en Europe et aux Etats-Unis. Il estime les hausses de prix causées par ces cartels entre 17% et 53%. Boyer et Kotchoni (2015) utilisent une base de données mise à jour de celle de Connor (2010) en enlevant les cas extrêmes, et montrent que l'augmentation moyenne de prix causée par une situation de cartel est autour de 20%. Connor et Bolotova (2006), Bolotova et al. (2007) et Werden (2003) parviennent à des estimations de l'ordre de 17% à 30%.

Dans la suite de cet article, nous considererons plusieurs scenarios dans lesquels k peut varier entre 5% et 30%.

3.4.1.3 La marge contrefactuelle m

La marge contrefactuelle, qui représente la marge qui aurait été pratiquée par l'entreprise en l'absence de cartel, est également difficile à observer. En suivant Allain et al. (2015), nous analysons plusieurs scenarios dans lesquels la marge en l'absence de cartel serait de l'ordre de 5% à 20%.

3.4.1.4 L'élasticité-prix de la demande ϵ

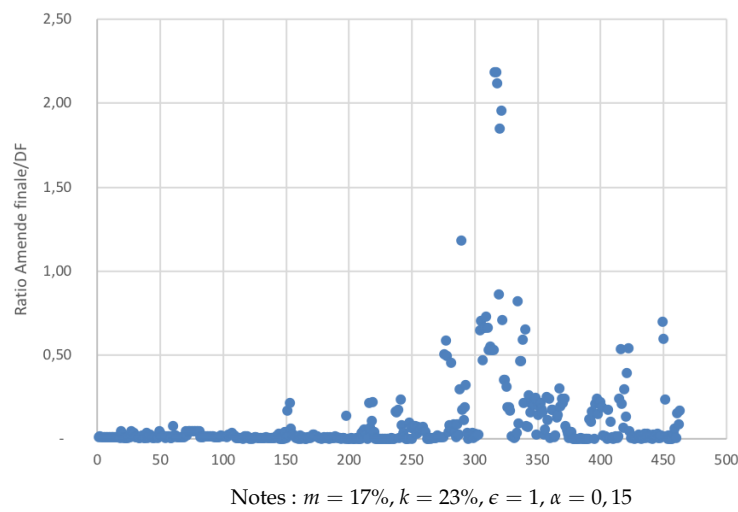
L'élasticité-prix de la demande est également un paramètre clé de l'estimation des dommages d'un cartel sur l'économie. L'Autorité de la Concurrence écrit ainsi: "afin d'apprécier l'importance du dommage causé à l'économie, l'Autorité s'attache à prendre en compte les caractéristiques économiques objectives du secteur en cause, dans la mesure où ces dernières sont de nature à avoir une influence sur les conséquences conjoncturelles ou structurelles des pratiques. En l'espèce, il convient d'apprécier successivement l'existence de barrières à l'entrée, l'élasticité-prix de la demande et le contre-pouvoir des distributeurs." Comme expliqué dans la section 3.3, nous disposons d'une estimation de l'élasticité-prix de la demande pour environ 40% des observations de notre base de données. Concernant les observations pour lesquelles nous ne disposons pas d'information, nous considérerons des scénarios raisonnables en faisant varier l'élasticité-prix entre 0 et 2.

3.4.2 Propriétés dissuasives des sanctions

Cette section est dédiée à l'analyse empirique des propriétés dissuasives des sanctions prononcées par l'Autorité de la Concurrence. Pour cette analyse nous fixerons la probabilité de détection (α) égale à 15%, et l'augmentation du prix causée par le cartel (k) sera comprise entre 5% et 30%, la marge contrefactuelle (m) entre 5% et 20% et l'élasticité-prix de la demande (ϵ) entre 0 et 2 pour les secteurs pour lesquels nous ne disposons pas d'estimations.

Pour chacune des 466 amendes initiales répertoriées dans notre base de données nous calculons l'amende théorique de dissuasion telle que définie par l'équation (1). Le graphique 3.4 trace, pour l'ensemble des entreprises de notre base de données, le ratio du montant de l'amende imposée par l'Autorité de la Concurrence sur le seuil de dissuasion théorique DF. Nous retenons pour les paramètres de l'analyse des valeurs dans la fourchette moyenne: $m = 17\%$, $k = 23\%$, $\epsilon = 1$, $\alpha = 0,15$.

Figure 3.4: Ratio de l'amende initiale sur DF.



Sous les hypothèses retenues, nous observons que la plupart des amendes effectives sont très en-dessous du seuil de dissuasion théorique. Seules six amendes sont supérieures au seuil de dissuasion. Il s'agit de 6 entreprises condamnées en 2012 pour 2 cartels, celui des farines alimentaires (12-D-09) et celui des granulats (12-D-06). Il est important de noter que la durée de ces cartels est plus élevée que la moyenne (65 mois) puis qu'elle varie entre 212 et 552 mois: dans la mesure où l'Autorité de la Concurrence utilise la durée du cartel dans la formule de calcul de l'amende de base, cette durée explique sans doute dans une large mesure l'importance du montant de l'amende. A l'inverse, 73% des amendes sont inférieures à 10% du seuil théorique de dissuasion (ratio inférieur à 0,1).

Ce premier aperçu semble donc indiquer que les amendes imposées par l’Autorité de la Concurrence sont loin du seuil de dissuasion. Ces résultats contrastent avec ceux obtenus, avec les mêmes méthodes, par Allain et al. (2015) sur les condamnations de la Commission Européenne. Dans cette étude portant sur 325 entreprises ayant participé à 49 cartels détectés et sanctionnés par la Commission Européenne entre 2005 et 2012, pour le même jeu de paramètres ($m = 17\%$, $k = 23\%$, $\epsilon = 1$, $\alpha = 0,15$), 39,1% des amendes prononcées étaient supérieures au montant théorique de dissuasion. Cependant, une tendance haussière du ratio étudié se dessine à partir du début de l’année 2012 (observation numéro 280).

Dans ce qui suit, nous analysons la sensibilité de ces premiers résultats aux variations des hypothèses concernant l’environnement concurrentiel du marché. Nous étudions comment varie le pourcentage d’amendes effectives qui satisfont le critère de dissuasion selon différents scénarios. Dans un premier temps, nous conservons l’hypothèse standard sur la probabilité de détection ($\alpha = 0,15$) et nous faisons varier l’élasticité prix de la demande entre 0 et 2. Les tableaux , et donnent le pourcentage d’amendes effectives supérieures au seuil de dissuasion dans ces cas, pour différentes valeurs de l’augmentation du prix liée au cartel k (en colonne) et de la marge contrefactuelle m (en ligne). Dans chaque cas, nous appliquons les mêmes hypothèses sur k , m et α pour tous les secteurs. L’élasticité-prix de la demande (ϵ) varie entre 0 et 2 uniquement pour les secteurs pour lesquels nous ne disposons pas d’estimations.

Table 3.3: Part des amendes initiales au dessus de DF entre 2006 et 2018 ($\epsilon = 0$, $\alpha = 0,15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	11%	6%	2%	2%
$m = 10\%$	12%	7%	2%	2%
$m = 20\%$	12%	7%	2%	2%

Table 3.4: Part des amendes au dessus de DF entre 2006 et 2018 ($\epsilon = 1, \alpha = 0,15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	11%	7%	2%	2%
$m = 10\%$	14%	7%	2%	2%
$m = 20\%$	16%	8%	3%	2%

Table 3.5: Part des amendes au dessus de DF entre 2006 et 2018 ($\epsilon = 2, \alpha = 0,15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	13%	7%	2%	2%
$m = 10\%$	16%	8%	3%	3%
$m = 20\%$	18%	8%	7%	12%

Dans l'ensemble, le pourcentage d'amendes supérieures au seuil de dissuasion est toujours faible: il varie de 2% à 18% selon les scénarios. Quelles que soient l'élasticité-prix de la demande et la marge contrefactuelle, plus k est faible, moins un cartel est profitable, et donc plus il est facile à dissuader. Cela explique pourquoi le pourcentage d'amendes au dessus du seuil de dissuasion augmente quand on prend une valeur de k plus faible. De même, plus la marge contrefactuelle du secteur, m , est élevée, moins le cartel est profitable: pour une amende donnée, un cartel sera moins stable si la concurrence dans le secteur est faible en l'absence de cartel. Enfin, le pourcentage d'amendes au dessus du seuil de dissuasion varie également avec l'élasticité-prix de la demande dans le secteur. Quand la demande est inélastique, le cartel est capable d'extraire plus de rente des consommateurs. Le profit dans le cas d'un cartel est donc plus important quand $\epsilon = 0$, ce qui rend le seuil de dissuasion plus difficile à atteindre. Cette situation est illustrée par le tableau 3.3 qui présente la part la plus faible, entre 2% et 12%, d'amendes au dessus de DF. Avec une élasticité-prix plus important, $\epsilon = 1$ (tableau 3.4) et $\epsilon = 2$ (tableau 3.5) nous constatons que le nombre d'amendes dépassant l'amende dissuasive augmente.

Dans le tableau 3.6, nous étudions la sensibilité de ce pourcentage à la définition de la probabilité de détection. Ce tableau illustre la faible sensibilité des résultats à des variations de la probabilité α de détection du cartel et du niveau de l'élasticité-prix de la demande.

Table 3.6: Part des amendes au dessus de DF entre 2006 et 2018 ($m = k = 20\%$)

	$\alpha = 10\%$	$\alpha = 15\%$	$\alpha = 20\%$
$\epsilon = 0$	2%	2%	2%
$\epsilon = 1$	2%	3%	5%
$\epsilon = 2$	3%	7%	3%

Les résultats exposés dans les tableaux 3.3, 3.4, et 3.5 indiquent que les propriétés de dissuasion des amendes imposées par L'Autorité de la Concurrence sont faibles : entre 2% et 18% des sanctions imposées à l'encontre des cartels entre 2006 et 2018 atteignent le montant minimal dissuasif. Il faut toutefois noter que la part des amendes situées au-delà du seuil DF est plus élevée si l'on considère uniquement les cartels sanctionnés après le 1er janvier 2012. Les tableaux 3.10, 3.11, 3.12 et 3.13 en Annexe 3.7.2 montrent que jusqu'à 42% des amendes imposées à partir de 2012 sont au-dessus du montant théorique de dissuasion: la proportion d'amendes dissuasives augmente, mais plus de la moitié des amendes reste en dessous du seuil de dissuasion.

Un point commun entre ces résultats et ceux de Allain et al (2015) est la forte hétérogénéité constatée dans les propriétés de dissuasion des amendes. Pour aller plus loin, nous reprenons l'analyse économétrique décrite dans la section 3.3.3 et l'adaptions à l'étude du ratio du montant de l'amende sur DF .

$$\begin{bmatrix} \ln\left(\frac{A_i^I}{DF_i}\right) \\ \ln\left(\frac{A_i^F}{DF_i}\right) \end{bmatrix} = \beta_0 + \beta_1 X_{2012} + \beta_{2,i} \begin{Bmatrix} X_i^{CA} \\ X_i^T \\ X_i^N \\ X_i^E \end{Bmatrix} + \beta_{3,i} X_i^{Cl} + \beta_{4,i} \lambda_i + \epsilon_i \quad (3.5)$$

Dans l'équation 3.5 ci-dessus, les variables expliquées $\ln\left(\frac{A_i^I}{DF_i}\right)$ et $\ln\left(\frac{A_i^F}{DF_i}\right)$ représentent, pour l'entreprise i , le logarithme du ratio de l'amende finale (respectivement de l'amende initiale) par rapport à l'amende dissuasive décrite par l'équation (3.2). Les variables explicatives sont identiques à celles de l'équation (3.4). Le tableau 3.7 suivant expose les résultats de cette regression.

Table 3.7: Part des amendes supérieures au seuil de dissuasion

	Amende Initiale/DF	Amende Finales/DF
Après 01/2012	1,702***	1,250***
Chiffre d'affaire	0.044	0,046
Durée	0,491***	0,508***
Nb. Entreprises	-0.110	-0.117
Elasticité	0.348*	0,348*
Clémence	1.087*	0.753
Secteur d'activité	Oui	Oui
Observations	466	466
Adjusted R^2	0.605	0.516

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Le tableau 3.7 ci-dessus confirme l'augmentation du ratio du montant de l'amende (finale ou initiale) par rapport à l'amende dissuasive après 2012. Le chiffre d'affaire n'explique pas significativement la valeur du ratio entre l'amende effective et l'amende de dissuasion. Or le tableau 3.2 mettait en évidence un fort effet du chiffre d'affaires sur le montant de l'amende; par ailleurs, le seuil de dissuasion DF est également proportionnel au chiffre d'affaires. L'absence d'influence du chiffre d'affaire sur le ratio semble indiquer que cette variable est correctement prise en compte dans le calcul des amendes par l'Autorité de la Concurrence. En revanche, la durée du cartel, qui est pris en compte dans les méthodes de calculs de l'Autorité de la Concurrence, mais qui n'apparaît pas dans le seuil théorique DF , explique significativement ce ratio: les cartels de longue durée sont condamnés à des amendes plus élevées, donc plus dissuasives.

3.4.3 Propriétés compensatoires des sanctions

Dans cette section, nous nous intéressons au caractère compensatoire des amendes. En suivant la définition retenue à la section 2, nous comparons le montant de l'amende au montant des gains accumulés par les membres du cartel pendant toute sa durée, CF .

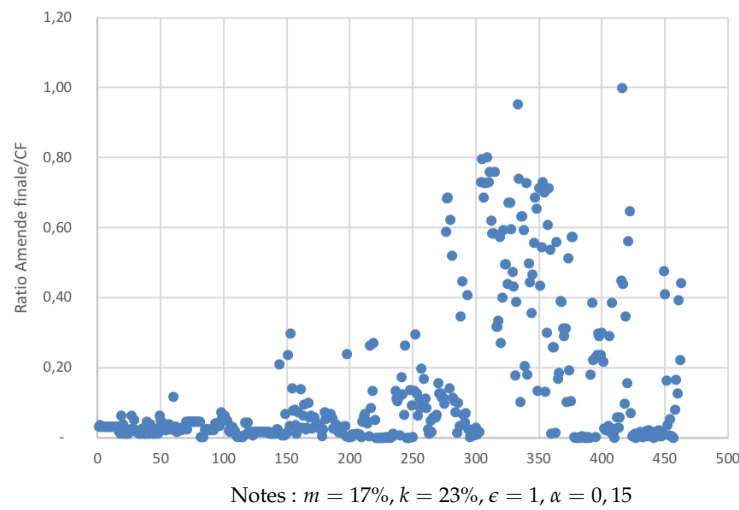
nous calculons dans cette section le nombre d'amendes initiales décidées par dont le montant est au dessus de l'amende théorique de compensation illustrée par l'équation (3.2).

Le graphique 3.5 ci-dessous trace, pour chaque entreprise condamnée par l'Autorité de la Concurrence, le ratio de l'amende sur le seuil CF . Les paramètres retenus sont les mêmes que précédemment ($m = 17\%$, $k = 23\%$, $\epsilon = 1$, $\alpha = 0,15$). Il est remarquable que ce ratio atteigne 1 pour une seule entreprise. Il s'agit d'une des trois entreprises ayant pris part au cartel des appareils de chauffage mobile à combustible liquide, dont l'amende totale infligée aux participants a atteint environ 9 millions d'euros.

De même que pour pour l'amende de dissuasion, nous observons sur le graphique une tendance haussière du ratio à partir du début de l'année 2012. Nous pouvons également noter que bien qu'une seule entreprise ait un ratio supérieur à 1, la dispersion des ratios semble plus importante sur ce graphique que sur le graphique 3.4: le nombre d'amendes situées entre la moitié du seuil et le seuil est plus important pour CF que pour DF .

Ces résultats sont confirmés par les tableaux 3.14, 3.15, 3.16 et 3.17 présentés en annexe 3.7.3. Ils montrent qu'en faisant varier les hypothèses de paramètres, la part des amendes réelles dont le montant est supérieur ou égal au montant des amendes compensatoires théoriques est compris entre 0 et 28%. A nouveau, plus k est faible, plus le ratio est élevé, car le cartel est moins profitable s'il engendre une faible hausse de prix. De même, plus la marge contrefactuelle du secteur, m , est élevée, plus le ratio est élevé, car le cartel est moins profitable. Enfin, le ratio augmente également avec l'élasticité-prix de la demande, ϵ , qui rend le cartel moins profitable.

Figure 3.5: Ratio de l'amende initiale sur CF.



Comme dans la section 3.4.2, nous reprenons l'analyse économétrique décrite dans la section 3.3.3 et l'adaptions à l'étude du ratio du montant de l'amende sur le seuil CF .

$$\begin{bmatrix} \ln\left(\frac{A_i^I}{CF_i}\right) \\ \ln\left(\frac{A_i^F}{CF_i}\right) \end{bmatrix} = \beta_0 + \beta_1 X_{2012} + \beta_{2,i} \begin{Bmatrix} X_i^{CA} \\ X_i^T \\ X_i^N \\ X_i^E \end{Bmatrix} + \beta_{3,i} X_i^{Cl} + \beta_{4,i} \lambda_i + \epsilon_i \quad (3.6)$$

La tableau 3.8 ci-dessous présente les résultats de l'estimation.

Table 3.8: Part des amendes supérieures au seuil de compensation

	Amende Initiale/CF	Amende Finales/CF
Après 01/2012	1.750***	1,160***
Chiffre d'affaire	0.0587	0,045
Durée	-0.339***	-0.284***
Nb. Entreprises	-0.096	-0.097
Elasticité	0.334*	0,314*
Clémence	1.326*	1.000
Secteur d'activité	Oui	Oui
Observations	466	466
Adjusted R^2	0.599	0.468

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Comme le tableau 3.7, le tableau 3.8 ci-dessus met en évidence l'augmentation du ratio du montant de l'amende (finale ou initiale) par rapport au seuil de compensation après 2012. De même, le chiffre d'affaire n'explique pas significativement la valeur du ratio entre l'amende effective et le seuil de compensation. En revanche, la durée du cartel explique significativement et de façon négative le ratio de l'amende par rapport au seuil de compensation. En effet, les gains du cartels sont proportionnels à sa durée, et le seuil de compensation CF est donc un multiple du nombre d'années d'exercice du cartel, n . Or, comme on l'a vu dans la section 3.2.1, l'amende de base est multipliée par un coefficient traduisant la durée de l'infraction de manière non-linéaire (1 pour la première année, auquel s'ajoute 0.5 pour chaque année supplémentaire). La prise en compte de la durée du cartel n'est donc pas suffisante pour assurer le caractère compensatoire de l'amende.

3.5 Conclusion

Cet article contribue à la littérature économique sur la prévention des cartels en analysant le caractère dissuasif et compensatoire des amendes imposées par l'Autorité de la Concurrence en France entre 2006 et 2018. Pour ce faire, nous avons construit une base de données originale qui regroupe les informations relatives à 466 sanctions financières imposées par l'Autorité de la Concurrence. L'élasticité-prix de la demande étant potentiellement un élément clé pour juger de l'impact d'un cartel sur l'économie, nous avons enrichi notre base de données d'une estimation de l'élasticité-prix pour plus de 40% des observations (187 entreprises). Partant de cette base de données, nous comparons les amendes réelles avec les seuils de dissuasion et de compensation théoriques développés par Allain et al. (2015). Alors, que, sur des données européennes, Allain et al. (2015) montrent que 30% à 80% (resp. 50 à 90%) des amendes infligées par la Commission Européenne entre 2005 et 2012 sont au-dessus du seuil dissuasif (resp. compensatoire), nous montrons au contraire que les amendes imposées par l'Autorité de la Concurrence entre 2006 et 2018 sont majoritairement sous-optimales. Seules 2% à 18% des sanctions sont au-dessus du niveau dissuasif théorique, et entre 0% et 28% des amendes sont au-dessus du niveau compensatoire. Cette écart de résultat montre qu'il existe une importante différence d'approche et de calculs entre ces deux autorités de concurrence. Ce résultats est toutefois à nuancer par l'augmentation relative des amendes imposées par l'Autorité de la Concurrence depuis 2012, la part des amendes dissuasives passant de 0% à 3% entre 2006 et 2011 à 3% à 42% entre 2012 et 2018.

3.6 References

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3.7 Annexes

3.7.1 Liste des cartels contenus dans notre base de données

Table 3.9: Liste des cas de cartels étudiés

Ref. Décision	Dénomination	Nbr. Entreprises	Amendes (M.€)
06-D-04	Parfumerie	16	45,44
06-D-07	Travaux Publics	34	48
06-D-09	Fabrication des portes	9	5
07-D-01	Travaux de canalisation	3	0,944
07-D-02	Traitement des déchets	3	2,148
07-D-15	Lycées Ile-de-France	12	47,31
07-D-16	Céréales	3	0,0811
07-D-21	Location-entretien du linge	8	18,21
07-D-26	Fourniture de câbles à haute tension	5	19,53
07-D-48	Déménagement	8	61,19
08-D-12	Production de contreplaqué	12	8,18
08-D-13	Nettoyage	4	1,68
08-D-15	Rénovation de chaufferies	5	0,052
08-D-22	Geometer experts	12	0,08
08-D-23	Taxi	5	0,037
08-D-29	Entretien de menuiserie	2	1,13
08-D-30	Approvisionnement en kérosène	5	41,1
08-D-32	Produits Métallurgiques	10	287,33
08-D-33	Autocar	11	1,17
09-D-03	Autocar	6	0,35
09-D-05	Emploi Interim	4	94,4
09-D-25	Travaux de voies ferrées	5	4,2
09-D-34	Travaux publics d'électricité	4	0,169
10-D-03	Profilage de fossés	5	0,092
10-D-05	Transports sanitaires	3	0,022
10-D-13	Container transport Le Havre port	4	0,52
10-D-22	Transports sanitaires	7	0,022
10-D-28	Retrait d'argent - Banque	24	384,92
10-D-35	Electrodes de soudure	4	0,101
10-D-39	Panneaux Signalétique	8	52,7
11-D-01	Manutention Portuaire La Réunion	3	0,07
11-D-02	Restauration de monu. historiques	14	9,59
11-D-07	Travaux de peinture	4	1,16
11-D-13	Travaux d'électrification	10	9,40
11-D-17	Lessives	3	367,9
12-D-02	Culture and tourisme	10	0,64
12-D-06	Granulat	5	0,38
12-D-08	Endives	10	3,65
12-D-09	Farines Alimentaires	19	242,12
12-D-27	Billeterie	6	9,37
13-D-03	Porc charcutier	5	4,51
13-D-12	Commodités chimiques	7	79,09
14-D-16	Déménagement des militaires	3	0,22
14-D-19	Produits d'entretien, d'hygiène et de soins	17	841
14-D-20	Papiers peints	4	5,27
15-D-03	Yaourts	10	192,7
15-D-04	Boulangerie artisanale	3	1,13
15-D-08	Viande de volaille	13	9,81
15-D-19	Transport terrestres	20	663,3
16-D-02	Transports terrestres	4	0,19
16-D-09	Construction	6	5,021
16-D-17	Chauffage mobiles	3	9,013
16-D-20	Mannequinat	25	1,80
17-D-20	Revêtements de sols résilients	3	302
18-D-15	Distrib. de médicaments vétérinaires	6	15,93
18-D-24	Produits électroménagers	6	189
Total		466	4029,75

3.7.2 Part des amendes au dessus de DF entre 2012 et 2018

Table 3.10: Part des amendes au dessus de DF entre 2012 et 2018 ($\epsilon = 2, \alpha = 0,15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	31%	17%	5%	5%
$m = 10\%$	39%	18%	8%	7%
$m = 20\%$	42%	18%	17%	30%

Table 3.11: Part des amendes au dessus de DF entre 2012 et 2018 ($\epsilon = 1, \alpha = 0,15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	27%	16%	5%	5%
$m = 10\%$	35%	16%	5%	5%
$m = 20\%$	39%	18%	6%	5%

Table 3.12: Part des amendes au dessus de DF entre 2012 et 2018 ($\epsilon = 0, \alpha = 0,15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	25%	15%	5%	3%
$m = 10\%$	29%	15%	5%	3%
$m = 20\%$	29%	15%	5%	3%

Table 3.13: Part des amendes au dessus de DF entre 2012 et 2018 ($m = k = 20\%$)

	$\alpha = 10\%$	$\alpha = 15\%$	$\alpha = 20\%$
$\epsilon = 0$	3%	5%	7%
$\epsilon = 1$	5%	6%	12%
$\epsilon = 2$	8%	17%	18%

3.7.3 Part des amendes au dessus de CF entre 2006 et 2018

Table 3.14: Part des amendes au dessus de CF entre 2006 et 2018 ($\epsilon = 0, \alpha = 0, 15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	26%	12%	0%	0%
$m = 10\%$	26%	13%	0%	0%
$m = 20\%$	26%	13%	1%	1%

Table 3.15: Part des amendes au dessus de CF entre 2006 et 2018 ($\epsilon = 1, \alpha = 0, 15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	26%	13%	1%	0%
$m = 10\%$	27%	14%	1%	0%
$m = 20\%$	27%	14%	2%	1%

Table 3.16: Part des amendes au dessus de CF entre 2006 et 2018 ($\epsilon = 2$, $\alpha = 0,15$)

	$k = 5\%$	$k = 10\%$	$k = 20\%$	$k = 30\%$
$m = 5\%$	27%	14%	2%	1%
$m = 10\%$	27%	15%	4%	3%
$m = 20\%$	28%	18%	12%	18%

Table 3.17: Part des amendes au dessus de CF entre 2006 et 2018 ($m = k = 20\%$)

	$\alpha = 10\%$	$\alpha = 15\%$	$\alpha = 20\%$
$\epsilon = 0$	1%	1%	1%
$\epsilon = 1$	2%	2%	2%
$\epsilon = 2$	12%	12%	12%

Table 3.18: Secteurs Industriels

	amende Initiale
Après 01/2012	1,590***
Chiffre d'affaire	0,936***
Durée	0,391***
Nb. Entreprises	0.017
Elasticité	-0,064
Clémence	1.722**
Secteur Alimentaire	Reference
Secteur Chimie	2.093***
Secteur Divertissement	0.8791*
Secteur Batiment	0.3703
Secteur Luxe	0.3714
Secteur Matiere premiere	1.104
Secteur Medical	-2.492***
Secteur Produit menager	1.526***
Secteur Service public	-0.8555
Secteur Services	0.4057
Secteur Transport	-0.1010
Secteur Travaux publics	0.2508
Secteur Niche	-1.087*
Observations	466
Adjusted R^2	0.7508

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.19: Tests de robustesse

	Initiale 2010	Initiale 2011	Initiale 2012	Initiale 2012
Après 01/2010	1,1871***			
Après 01/2011		1,357***		
Après 01/2012			1,445***	
Après 01/2013				0.1399
Chiffre d'affaire	0,9373***	0,9334***	0,9382***	0,9146***
Durée	0,4808***	0,4878***	0,4338***	0,4264***
Nb. Entreprises	0.1826	0.0330	-0.0320	0.1446
Elasticité	-0,3024	-0,1072	-0,1316*	-0.4260 *
Secteur d'activité	Oui	Oui	Oui	Oui
Observations	466	466	466	466
Adjusted R^2	0.788	0.794	0.795	0.767

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Titre : Essais sur l'application des théories microéconomiques à l'analyse des structures de marché

Mots clés : Parité tarifaire, Plateforme de réservation en ligne, Discrimination tarifaire, Analyses économétriques, Économie Industrielle

Résumé : Les notions de plateforme, de marché bifaces ou même multi-faces sont aujourd'hui au cœur des discussions économiques du fait de l'explosion du e-commerce lié à l'essor des nouvelles technologies de l'information. Ces plateformes en lignes offrent de nouvelles opportunités et soulèvent de nombreuses questions (stratégie tarifaire, réglementation, etc.). Les deux premiers chapitres de cette thèse s'intéressent aux plateformes de réservation en ligne et plus particulièrement à l'impact concurrentiel des clauses de parités tarifaire. Ces dernières, mises en place par les plateformes, imposent aux vendeurs de proposer son bien ou service via la plateforme au meilleur prix disponible sur tous les autres canaux de ventes.

Dans le premier chapitre, je montre que, d'un point de vue théorique, l'effet concurrentiel des clauses de parité est majoritairement négatif mais peut devenir positif en fonction du pouvoir de négociation de chacun des acteurs.

Dans un second temps, une analyse empirique reposant sur une base de données unique de plus de 6 millions de prix, me permet de montrer que la suppression des clauses de parité à Paris a engendré une baisse tarifaire moyenne des hôtels de -3,1% à -4,5%. Cette baisse peut en partie s'expliquer par une augmentation des stratégies de discrimination tarifaire. En effet, les hôtels ont augmenté de 1,4 à 2,3% la discrimination entre plateformes et ils ont augmenté de 2,1% à 3,6% leurs stratégies de discrimination inter-temporelle.

Le dernier chapitre de cette thèse est dédié à l'analyse des amendes décidées par l'Autorité de la Concurrence entre 2006 et 2018 pour des pratiques de cartels. Nous montrons que ces amendes sont sous optimales car elles ne satisfassent pas les critères de dissuasion et de compensation.

Title: Topics in Industrial Organization applied to Competition Policy

Keywords: Price Parity Agreement, Online Booking Platforms, Before-after econometrics design, Price Discrimination, Industrial Organization.

Abstract: The Internet technology and the web economy create new types of markets and new relationships between market players.

The majority of these new markets can be associated to platforms where two or more sides of the same market meet. Such "multi-sided" industries raise specific issues. Determining the optimal pricing strategy for both the platform and the users selling goods through the platform is one of the main challenges of this new economy.

The first two chapters of my thesis analysis Price Parity Agreement (PPA) from a theoretical and an empirical point of view.

I first study the effect of Price Parity Agreements from a theoretical perspective. I demonstrate that PPAs on the online booking market are detrimental to consumers if platforms have most of the bargaining power. They attenuate competition between platforms, lead to higher commission fees and higher hotel rooms' prices. However, MFN clauses may also be welfare improving when hotels own the bargaining power and competition between them is high.

The second chapter is dedicated to an empirical analysis of the effects of PPAs. Using a before-after design and controlling for external shocks, I demonstrate that the end of Price Parity Agreements imposed by public authorities to OTAs causes a decrease of about 3.1% to 4.5% in the average level of prices set by hotels. This decrease may be explained by an increase of price discrimination. I show that the level of price discrimination across OTAs increases by 2.3% to 1.4% after the drop of Price Parity Agreements and that the degree of inter-temporal price discrimination also increases by 3.6% to 2.1%.

The last chapter of my thesis is focused on the analysis of the financial fines imposed by the French Autorité de la Concurrence to cartels in France between 2006 and 2018. We show that the level of these fines is sub-optimal and doesn't meet the deterrence objective in the majority of the cases.

