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The Price Effects of Prohibiting Price Parity Clauses: Evidence from International Hotel Groups*

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Abstract

Dominant platforms such as Booking.com and Amazon often impose Price Parity Clauses to prevent sellers from charging lower prices on alternative sales channels. We provide quasi-experimental evidence on the removal of these price restrictions in France in 2015 for three major international hotel groups. First, our analyses reveal limited and non-significant price effects for rooms sold through channels visible to consumers, such as the hotels' websites or Online Travel Agencies. Second, we document a significant price reduction on sales channels not visible to consumers, such as the hotels' direct offline channel. Third, we identify a significant shift in sales share from online travel agencies to the hotels' direct offline channel.

JEL: D40, K21, L10, L42, L81.
Keywords: price parity clauses, online travel agents, platform regulation, hotel pricing.

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1 Introduction

In today's highly digitized economy, goods and services can be purchased directly from sellers or through intermediary platforms. In online markets, the contractual relationship between the involved parties often follows the agency model, whereby sellers decide the final prices displayed on each sales channel, including those shown on platforms. For every intermediated transaction, platforms receive a commission fee, which is usually proportional to the transaction's price. For example, hotels can offer rooms on their own website or through Online Travel Agencies (OTAs) such as Booking.com or Expedia. If a room is reserved through an OTA, the hotel will pay a commission fee to that OTA. It is, therefore, in the platforms' best interest to maximize the number of transactions that consumers finalize through them, and for this purpose, they may adopt specific contractual arrangements that could raise concerns.

Controversial arrangements at the center of regulatory scrutiny are Price Parity Clauses (PPCs), namely price restrictions imposed by platforms on client sellers. These clauses stipulate that the latter cannot charge lower prices on alternative sales channels. PPCs are widespread in the e-commerce and lodging sectors, but they also exist in industries such as entertainment, insurance, and payment systems. The so-called "wide" PPCs mandate that the price charged by sellers cannot be lowered on *any* alternative sales channel. "Narrow" PPCs are less rigid, allowing sellers to lower prices on rival platforms, but not when selling directly.

Platforms affirm that PPCs are necessary to prevent showrooming, where consumers initially browse the platforms to find their preferred seller but then switch to the seller's direct channel to obtain discounts. This practice, if widely adopted by consumers, could render platforms' activity unprofitable, possibly undermining their existence. Another important argument presented by platforms in defence of PPCs is that showrooming may undermine their incentive to invest in improving the quality of the services provided to both sellers and consumers.

On the other hand, competition authorities and regulators claim that PPCs reinforce the dominant position of leading platforms and contribute to higher prices for consumers. Indeed, if sellers cannot differentiate prices, consumers are more likely to make purchases through platforms, which generally offer additional benefits. Platforms can then impose relatively high commission rates and extract a large portion of the sellers' profits. Conversely, if PPCs were removed, sellers could lower prices when selling directly or on rival platforms, thereby limiting the dominant platforms' ability to charge excessive fees.

This article focuses on the lodging sector and investigates the effects of prohibiting all types of PPCs. We exploit the first-of-its-kind policy change that occurred in France in 2015, the Macron Law. Our unique and comprehensive dataset covers three years, from July 2014 to June 2017, and consists of monthly transaction data for 166 hotels belonging to three major international groups. These hotels span 61 cities in seven European countries and employ multiple channels to sell their rooms, among which are major OTAs. Interestingly, we also have information about OTA commission rates for two hotel groups.

Methodology and Results. We employ quasi-experimental methods to empirically estimate the impact of the full prohibition of PPCs in France on hotel prices and room sales shares across various channels. In our study design, hotels in France constitute the treated group, and the hotels in other EU countries, where PPCs were still allowed, serve as the control units. The results indicate that the prohibition of PPCs had no significant effects on room prices on OTAs or hotel websites—two online channels where price information is “visible” to everyone. However, a significant 5.7% price reduction was identified on the hotels’ primary offline channel, which includes bookings made through direct phone calls, emails, and walk-ins. Price information for this channel is “non-visible” to outsiders, as hotels process these transactions internally. For a typical transaction in our sample, this translates into a price reduction of approximately 8.5 euros per booking in France. Regarding room sales, our findings reveal a significant decrease in the share of sales on OTAs, coupled with an increase in the direct offline channel. In France, bookings via the OTA channel experienced a relative decline of 2.1% compared to the controls, whereas bookings made through the main offline channel increased by about 4.5%.

There could be several reasons for these findings. Concerning the visible channels, hotels might be hesitant to conspicuously differentiate prices, as this may induce potential retaliation from platforms. Hunold, Kesler and Laitenberger (2020) demonstrated that OTAs tend to downlist hotels that set lower prices elsewhere, a practice known as “dimming”. Peitz (2022) suggested that platforms can adjust their recommendation algorithms to enhance the visibility of hotels with higher conversion rates from consumer queries. This is because low conversion rates are potentially associated with hotels offering more attractive prices outside the platform.[1] However, since OTAs can only monitor prices posted online, hotels had the opportunity to offer lower prices on their direct offline channel, and this was the observed behavior. Consequently, in relative terms, more bookings were finalized offline after the ban on PPCs. Nevertheless, we do not observe a significant post-policy expansion in the number of room-night reservations for French hotels in our sample.

Given the identified changes in both the prices and shares of the offline sales channel, we also estimate the consumer welfare implications of the Macron Law on the *population* of 3-star to 5-star French hotels. Using recently developed techniques to calculate robust welfare bounds for various consumer groups (Kang and Vasserman, 2022), we find non-negligible savings. In the sampling period of our study, we estimate that consumers who booked the 6,000 French 3-star hotels directly through the offline channel saved up to 90 million euros, while similar consumers who visited the 2,000 4-star and 5-star hotels saved over 120 million euros.

Our findings are relevant for at least two reasons. First, they suggest that the clientele of hotels may be segmented, with a share of users willing to make an extra effort to get better prices by directly contacting the hotel. Second, our results indicate that the primary pro-competitive effect of the policy reform did not occur on the OTAs’ or the hotels’ websites, as previously suggested by most economic and policy literature (see, among others, Edelman and Wright, 2015, Johnson, 2017, Baker and Scott Morton, 2018), but rather on the main offline channel where consumers can directly contact the hotels. Albeit less visible, this channel constitutes a substantial share of hotel transactions, wherein we identify significant price reductions and higher sales. Notably, without access to proprietary data, researchers and analysts may only gain a partial insight into the effects of such policy changes.

[1] Another response from OTAs to the prohibition of PPCs could be the introduction of preferred partner programs (PPPs), where price parity serves as the counterpart for top-listed sellers (Cazaubiel et al., 2022).

Finally, we would like to highlight the policy implications of our results. Overall, dominant OTAs seem to have found ways to convince hotels to respect price parity for the prices posted online, even without a formal contractual obligation. On this aspect, the prohibition of PPCs might have been ineffective in their intended areas. This issue is not specific only to the lodging sector. Still, it occurs more generally, as exemplified by Amazon's tactic to remove the "Buy Box" option for those products with lower prices offered elsewhere (Hunold, Laitenberger and Thébaudin, 2022; Scott Morton, 2023). In this context, our study supports the view that additional provisions should be included in regulations aiming at countering the dominant position of large platforms, thus making the entire market more transparent and competitive.

Institutional Context. The past decade has been characterized by a series of policy interventions against PPCs, especially when they are adopted by dominant platforms. In 2013, Amazon was forced to remove PPCs in the EU following antitrust investigations in Germany and the UK, then in the US in 2019 due to mounting political pressure. In November 2020, the UK Competition and Markets Authority (CMA) issued an unprecedented fine of almost £18 million against an insurance price comparison website for its use of wide PPCs. Booking.com and other major OTAs switched from wide to narrow PPCs in the EU in 2015 and in Australia and New Zealand in 2016, following investigations by competition authorities and consumer watchdogs. In some EU countries, narrow PPCs were also prohibited, starting from France in 2015, and continuing with Germany and Austria in 2016, Belgium and Italy in 2017, and Switzerland in 2022.

PPCs remain a central issue of interest for policymakers dealing with the challenges posed by dominant digital platforms, with explicit *ex-ante* bans of these clauses currently being discussed and implemented. In May 2021, the German Federal Court of Justice ruled that narrow PPCs violated antitrust laws, thus confirming the decision of the Federal Cartel Office in 2015 to prohibit all types of PPCs. In November 2021, the UK CMA recommended that wide PPCs be included in the list of hardcore restrictions in revising the Vertical Agreements Block Exemption regulation (Marshall, Albrighton and Kim, 2021). In addition, starting from March 2024, the Digital Markets Act (DMA) of the European Commission prohibits very large platforms from using all types of PPCs.[2] Amazon has already been designated as gatekeeper, and it is likely that some of the leading OTAs may also attain similar designation in the near future.

Related Literature and Contribution. Theoretical papers agree that prices are expected to decrease following the removal of PPCs (Edelman and Wright, 2015; Boik and Corts, 2016; Johnson, 2017; Wang and Wright, 2020), both in direct channels and on platforms. The absence of PPCs should enhance competition between sales channels, leading to lower commission rates that are passed through to prices. In fact, following the contractual change, sellers may be able to renegotiate their agreements with platforms, paving the way for price adjustments. In this respect, affiliation to a chain is usually associated with a better managerial organization (Kosová and Lafontaine, 2012; Hollenbeck, 2017), and this should guarantee higher bargaining power when contracting commission rates with the platform.

Recent empirical contributions, however, do not provide conclusive evidence. On the one hand, Hunold et al. (2018) and Ennis, Ivaldi and Lagos (2023) show that the (partial or full) removal of PPCs increases the likelihood that direct channels feature the lowest price. The

[2] See Article 5.3 of the DMA, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32022R1925.

former article compares trends in different countries following Germany's ban of any form of PPCs for Booking.com in 2015. The latter, using data from the EU and worldwide in 2014 and 2016, studies the main events of 2015, namely, the switch from wide to narrow PPCs in the EU and the full removal of PPCs in France and Germany. They find that regulating PPCs resulted in the direct channel being more likely to be cheaper than OTAs only for certain hotel categories.

On the other hand, a report commissioned by the EU in 2016 (European Competition Network, 2017) found scarce evidence of price differentiation across sales channels after the policy interventions of 2015. Moreover, in an investigation by the Bundeskartellamt, three major OTAs revealed that they did not change their standard commission rates following the authority's ban on narrow PPCs in 2015 (Bundeskartellamt, 2020). Finally, Mantovani, Piga and Reggiani (2021) examined the effect of the full removal of PPCs in France in 2015 using web data scraped from Booking.com for Corsica and Sardinia, two holiday destinations in France and Italy. They found a limited response to prices posted by hotels on Booking.com, both in the short and medium run. They showed, however, that chain hotels displayed a more pronounced price reaction.

Summing up both theoretical and empirical findings, there remains a degree of uncertainty regarding the actual effects of the policy changes introduced in different EU countries over the past years on hotel prices. It has been argued that the prohibition of PPCs may have favored more organized units, such as chain hotels, while small and independent hotels may have found it more difficult to break free from the influence of dominant platforms. Our findings reveal, instead, that the difficulty in taking advantage of the policy change may be widespread, with only consumers booking directly and offline benefiting from lower prices. While further research is important for testing this regulatory mechanism in the context of the DMA and other similar policy interventions, our paper is highly policy-relevant and can help pave the way for more research in this area.[3]

This article reports novel empirical estimates of the price effects of removing PPCs. We focus on France, the first country to prohibit all types of PPCs in the lodging sector, and extend beyond the previously discussed articles in four ways. First, we exploit a uniquely detailed proprietary database with channel-level transaction information from three major international hotel groups, which enables us to analyse the effects of the policy on both online and offline channels. Second, our data allows us to measure the price and sales changes across different channels rather than the probability of one particular channel (e.g., the official website) offering the lowest price. Hence, we are the first to study the effects of the prohibition of PPCs on prices and sales channel shares. Third, we exploit partial yet unique information regarding the commission rates of OTAs to relate the price changes with possible rate reductions following the policy intervention. Fourth, we employ recently developed estimators from the difference-in-differences (DID) and Machine Learning literature (Athey et al., 2021; Borusyak, Jaravel and Spiess, 2023) and provide robust consumer welfare bounds for our results (Kang and Vasserman, 2022).

Overall, Mantovani, Piga and Reggiani (2021) is the closest article to ours, as it exploits the same quasi-experimental setting. However, we extend their work in several aspects. First,

[3]Most-Favored Customer clauses are a related practice that guarantees refunds to buyers in case future discounts become available on the product they purchased. Chen and Liu (2011) find that these clauses diminished prices in the context of e-commerce, whereas Feng, Hwang and Maini (2023) report opposite findings in the health sector.

while they only focused on two islands in France and Italy, our study covers hotels in 61 cities and resort destinations across seven EU countries. Although their sample consisted of a higher number of lodging establishments, we believe the limited geographical coverage made it less representative than our study. Furthermore, we employ a range of newly introduced estimation methods, as highlighted above. This enables us to go beyond standard two-way fixed effects techniques and demonstrate the robustness of our main findings. Finally, the data used in this article are proprietary and cover sales on all of the hotels' channels, and not just the price offers posted on one OTA, Booking.com. In fact, our data reveals that OTAs accounted for less than 20% of hotel sales during the study period. Our current sample allows us to shed light on less monitored offline channels, which have been overlooked in previous literature and policy discussions. Indeed, we show that the most significant price and sales share effects occurred in the primary offline channel.

Our work also contributes to the recent empirical evidence on the impact of regulation on online platforms, including Facebook (Benzell and Collis, 2022), Instagram (Ershov and Mitchell, 2024) and Amazon (Gutierrez, 2022). Gutierrez (2022) shows that interventions that eliminate either the Prime program or product variety may decrease welfare, whereas increasing competition in fulfillment services, while preserving Prime and variety, may enhance it. A series of recent articles provide evidence related to some of the EU's DMA restrictions as, for example, the ban on self-preferencing (Chen and Tsai, 2023; Farronato, Fradkin and MacKay, 2023 and Reimers and Waldfogel, 2023) and search engine defaults (Decarolis, Li and Paternollo, 2023).

Structure. The remainder of the article is as follows. In Section 2, we propose a simple model to formulate theoretical predictions on the prohibition of PPCs on visible and non-visible sales channels. In Section 3 we present the data and the summary statistics, whereas in Section 4 we discuss our empirical strategy and identification approach. In Section 5, we present our main results on the price effects of prohibiting PPCs, whereas in Section 6, we explore the mechanisms and the possible heterogeneous effects of the policy change on the establishments in our sample. Section 7 tries to understand the implications of our findings and provides an estimate of the consumer welfare effects of prohibiting PPCs. Finally, Section 8 concludes.

2 The Economic Effects of Removing PPCs

Our investigation aims to evaluate the effects of removing PPCs on the hotels' sales channels, including both channels that are visible to everyone, such as OTA websites or a hotel's official website, and channels visible only to transaction parties (in this case, the hotel and its clients).

To understand the mechanisms underlying the removal of PPCs, we consider a stylized model in which n hotels, denoted by i ($i = 1, \ldots, n$), sell their rooms through three channels. These channels are indexed by $j = o, w, m$, where o represents OTAs, w denotes the hotels' official website, and m refers to the offline channel, encompassing hotel direct bookings via email, calls, or walk-ins. It is important to note that, according to our previous discussion, prices for the first two channels are visible, whereas the third one is not. There is no cost associated with selling through any of the channels, but selling on o involves paying OTAs a percentage rate, f_o, per transaction. Additional details regarding this model and its analysis can be found in Appendix A.

The demand function for a hotel-channel pair is specified according to a demand system *à la* Singh and Vives (1984), which has been extended and used in the context of platforms by Johansen and Vergé (2017), Calzada, Manna and Mantovani (2022), and Karle, Peitz and Reisinger (2020), inter alia. In this system, the market is not fully covered, allowing the overall demand to either expand or contract in response to price changes. Compared to these works, our framework goes beyond the dualism between the OTA and direct online channels by also considering a channel that is not publicly observable.

The results of our analysis relate to the price sensitivity of customers across different channels. To begin with, even for given OTAs' commission rates, the prohibition of PPCs intensifies the competitive pressure across channels. Specifically, we demonstrate that, in the absence of PPCs, prices across all three channels may decrease compared to the price with PPCs, represented by p^*.[4] This holds true even if there were *no variations* to the OTAs' rates following the removal of PPCs. If OTAs' rates were to decrease due to increased competition, then the cost of using that channel for the hotel would also decrease, making it more likely that the lower rate would be reflected in a lower room price.

Second, if consumers opting for channel m, which remains invisible to outsiders, exhibit higher price sensitivity, then the price on the non-visible channel will be lower than on the hotel website, $p_m^* < p_w^*$. A higher price sensitivity may be related, for example, to these customers' greater willingness to make the effort of writing an e-mail or calling the hotel. Finally, OTAs' commission rates, f_o, effectively raise the marginal cost from the hotels' perspective. Absent any price restriction due to the imposition of PPCs, this results in a higher equilibrium price for OTAs than the hotel website, $p_w^* < p_o^*$.

These findings are graphically illustrated through the numerical example in Figure 1. Focusing on a market with two hotels, the figure plots the first order conditions (FOCs) for all sales channels, as a function of the price p_i. The equilibrium prices require FOCs to be zero, and they can be identified in the figure where the functions intersect the horizontal axis.

The above discussion leads us to formulate the following testable hypotheses. First:

Theoretical Prediction 1. *Even in the absence of any reduction in OTAs' rates following the prohibition of PPCs, the equilibrium price under PPCs can still exceed that of all other sales channels once these clauses are prohibited. Moreover, if the OTAs' rates were to decrease, it would be more likely to obtain equilibria characterized by:* $p^* > \max\{p_o^*, p_w^*, p_m^*\}$.

Moreover:

Theoretical Prediction 2. *If PPCs are prohibited, the expected ranking of the equilibrium sales channel prices is* $p_m^* < p_w^* < p_o^*$*, provided that* (i) *consumers on the non-visible channel* m *are more price sensitive, and* (ii) *the demand on OTAs' channel* o *is less sensitive than that of the hotel website* w.

[4] Indeed, PPCs typically stifle price competition across channels because all prices for a room need to be the same. A hotel selling on a channel with lower costs cannot pass those through to consumers in the form of lower prices, without also lowering the price of a room on OTAs, which have higher rates (Scott Morton, 2023).

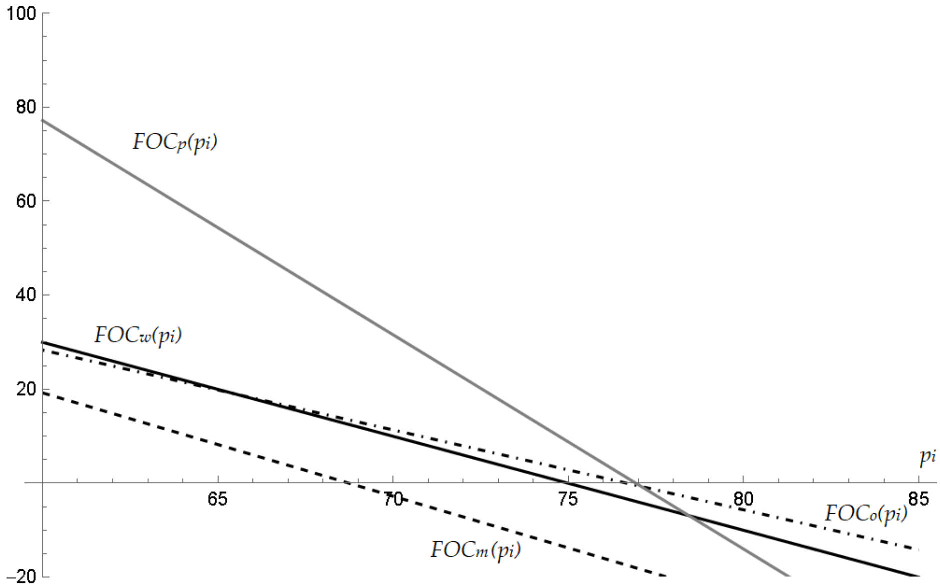


Figure 1: First-order conditions and equilibrium prices when PPCs are imposed (gray) and when they are removed (black). Example based on: $n = 2$, $\alpha = 100$, $\beta_0 = 1$, $\beta_1 = 0.1$, $\tau_m = 0.1$, $f_o = 0.15$. The symmetric equilibrium prices are: $p^* = 76.92$, $p^*_o = 76.66$, $p^*_w = 74.98$, and $p^*_m = 68.73$, respectively.

3 Data

Our empirical analysis is based on transaction data from 166 individual hotels from 61 cities in 7 European countries. These hotels are affiliated with 18 chain brands belonging to three major international hotel groups. Our sample covers three years, from July 2014 to June 2017. An observation in the data is a unique hotel/month/distribution channel combination. Each observation features the number of rooms booked, the length of stay, the reservation channel, and the revenue generated through each channel. From these data, we were able to calculate the total room nights booked per transaction and the average price per room night. Room night is a standard statistical metric in the hotel industry. At the hotel level, further information is available about the star ratings, the number of hotel rooms, the review score on OTAs, and additional hotel features and amenities (restaurant, bar, spa, etc.).

This study focuses on three channels: two online channels – Online Travel Agency (OTA) and Official Website (WEB) – and one offline channel, Offline Direct (INN). These channels are directly affected by the initial imposition and subsequent prohibition of PPCs. Together, they constitute approximately 80% of all reservations made to the hotels in our sample. We calculate the sales share of each reservation channel and provide additional information about the data in Appendix B.

Table 1 reports the summary statistics for the main variables in our dataset, providing information for individual countries and overall. Notably, during our sample period, France experienced policy changes related to PPCs. Hotels in the remaining six countries serve as control units. On average, hotels in our sample have 4.0 stars and a capacity of approximately 192 rooms. Review scores are quite similar, with an average of 8.4 on OTAs. Each hotel sold approximately 3,883 room nights per month, with an average room price of around 146.6 EUR.

Also, notice that prices in France are higher than the sample average.

Finally, to study the consumer welfare implications of our findings, we also obtain data on the population of French and European hotels from several sources, including France's National Institute of Statistics and Economic Studies (INSEE), Directorate General for Enterprises (DGE), and Eurostat.

Table 1—Summary Statistics of Hotel Characteristics By Country

	Star Ratings	Hotel Capacity	Room Nights	Review Score	Average Price	Occupancy Rate
France	4.1	166.2	3110	8.3	189.4	0.60
(n = 4438, N = 23)	(0.6)	(102.6)	(1102)	(0.5)	(67.3)	(0.16)
Control	3.9	196.3	4008	8.4	139.7	0.67
(n = 26521, N = 143)	(0.6)	(132.8)	(1346)	(0.4)	(44.7)	(0.16)
Belgium	3.6	160.3	3026	8.3	119.4	0.62
(n = 3171, N = 18)	(0.6)	(87.6)	(985)	(0.3)	24.4)	(0.15)
Italy	4.0	192.3	3550	8.3	137.8	0.62
(n = 5799, N = 32)	(0.5)	(111.4)	(1545)	(0.3)	(49.2)	(0.18)
Netherlands	4.1	191.7	4070	8.5	171.9	0.69
(n = 4114, N = 21)	(0.7)	(102.5)	(1204)	(0.4)	(57.1)	(0.15)
Portugal	4.1	161.4	3147	8.4	117.5	0.64
(n = 3001, N = 16)	(0.7)	(53.9)	(1213)	(0.4)	(57.8)	(0.19)
Spain	3.8	170.5	3264	8.2	109.8	0.67
(n = 3903, N = 22)	(0.7)	(95.4)	(1277)	(0.3)	(34.8)	(0.17)
United Kingdom	3.9	254.9	5806	8.5	162.2	0.75
(n = 6533, N = 34)	(0.6)	(203.8)	(1489)	(0.4)	(38.1)	(0.12)
Overall	4.0	192.1	3883	8.4	146.6	0.66
(n = 30959, N = 166)	(0.6)	(129.2)	(1315)	(0.4)	(48.5)	(0.16)

Note: This table reports the mean hotel characteristics of each country, as well as the overall mean. Standard deviations are reported in parentheses. France is the only country that experienced the treatment, which occurred in Month 15. The hotels of the other countries serve as control units. The observations are denoted using lowercase n, while the number of hotels is indicated using uppercase N. "Star Rating" reports each hotel's average number of star ratings. "Hotel Capacity" denotes the average number of rooms per hotel. "Room Nights" indicates the average monthly room-night sales of each hotel. "Review Score" reports each hotel's static average review score displayed on OTAs. The "Average Price" column reports the average price per room sold in each hotel.

4 Empirical Strategy

We exploit a major legislative change in the European hospitality sector to provide evidence on the effects of prohibiting PPCs. On August 6th, 2015, France enacted the "Macron Law", thus becoming the first country in the world to ban all types of PPCs imposed by OTAs on affiliated hotels (Roskis and Strange, 2015). According to competition authorities and the discussed economics literature, whose focus has been on the visible channels, eliminating PPCs should significantly lower hotel prices, especially in the direct online channel (hotel website). In addition, our analysis, which includes a non-visible booking channel, suggests that prices may decrease on both visible and non-visible sales channels when PPCs are prohibited (Theoretical Prediction 1). Further, under certain conditions on the average price sensitivity of customers in different channels, the prohibition of PPCs may induce prices to decrease more in the non-visible offline direct channel than in the visible online direct channel and the OTAs channel, respectively (Theoretical Prediction 2). Since our dataset contains the finalized transactional information for each booking channel per month, we explore the legislation's effects on hotel prices and room sales across the three channels.

For our identification strategy, we exploit the time dimension of our dataset by considering the outcome variables of interest *before and after* the Macron Law of August 2015. We also exploit variation in the units, with French hotels being the *treated* group, whereas hotels in the never-treated countries are the *control* group. Due to the Paris terrorist attacks on November 13th 2015, which produced a lingering and negative demand shock for accommodations in the French capital (Insee, 2016, Table 1), in our main specifications, we focus on estimates that exclude Parisian hotels.

Two-Way Fixed Effects. Since our paper focuses on a single, non-staggered treatment event, we began our analyses with a standard two-way fixed effects (TWFE) design:

$$Y_{it} = \delta_i + \gamma_t + \tau^{\text{TWFE}} D_{it} + \varepsilon_{it}, \tag{1}$$

where i identifies a unique hotel-channel combination, and t denotes the month. The outcome variables that we consider are $Y_{it} \in \{\ln(p_{it}) \times 100, s_{it} \times 100\}$. The former is the natural logarithm of the monthly channel price, and the latter is the percentage share of total bookings finalised through each channel. We multiply both outcome variables by 100 for an easier interpretation of the results. The variable δ_i is a hotel fixed effect, and γ_t is a cumulative monthly dummy variable to account for seasonality. The term D_{it} equals 1 if unit i in month t is "treated", i.e., subject to the Macron Law. The term ε_{it} is the error term. The coefficient of interest is τ^{TWFE}, which captures the average treatment effect on the treated units (henceforth, ATT), namely, the change in the outcome variables for French hotels after the Macron Law *vis-à-vis* the counterfactual case where the legislative ban on PPCs did not occur.

Our identification relies upon three main assumptions. First, only French hotels received a major exogenous "shock" – the Macron Law. Nonetheless, we exclude Parisian hotels from our main analyses, as hotel prices and room sales (channel shares) in the French capital may have been affected by both the Macron Law and the November 2015 terrorist attacks. Since these two events are relatively close chronologically, it would be impossible to isolate the price effects of one event from the other. Moreover, control hotels are also assumed to be unexposed to exogenous shocks.

Second, we assume that there are no anticipation effects in all pre-treatment periods. As regulatory interventions are announced before promulgation, we formally consider this issue when discussing the results and provide robustness checks that analyse the potential anticipatory and lagged effects.

Third, in the absence of the Macron Law, the potential trend of French hotel prices and room sales (channel shares), would follow on average a similar trajectory to those in the control group (parallel trends). To gauge evidence for this assumption, we employ the following *event study* specification:

$$Y_{it} = \delta_i + \gamma_t + \sum_{t=-13,\, t \neq -1}^{22} \beta_t M_{it} + \varepsilon_{it}, \tag{2}$$

where δ_i is the hotel fixed effect, and γ_t is the month fixed effect. The dummy variables M_{it} switch on if the Macron Law is t months away and if unit i is treated. The coefficients β_t are estimated for the "leads" and "lags" of the dynamic specification, with β_{-13} to β_{-2} regarded as the "pre-trends" and β_0 to β_{22} interpreted as the dynamic path of the ATT. The error term is ε_{it}. By convention, the coefficient of period -1 is normalized to 0.

Finally, to tackle the well-known issues of biased standard errors in DID models (Bertrand, Duflo and Mullainathan, 2004), we follow Angrist and Pischke (2008) and cluster the standard errors at a higher level of aggregation, namely, the city.

DID Imputation (Borusyak, Jaravel and Spiess, 2023). To strengthen the robustness of our empirical strategy, and given the well-documented issues of the TWFE design (de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021, among others), we adopt the methodology developed by Borusyak, Jaravel and Spiess (2023). This estimator employs a framework of imputation of the counterfactual, and the authors show it leads to non-trivial efficiency gains under various circumstances. The ATT is estimated in the following three steps:

1. Estimate the Y_{it} model using only the control units and obtain $\hat{\lambda}_i$ and $\hat{\delta}_t$ from:

$$Y_{it} = A'_{it}\lambda_i + X'_{it}\delta_t + \varepsilon_{it}; \tag{3}$$

2. Impute the counterfactual $Y_{it}(0)$ for treated units and calculate treatment effects τ as:

$$\hat{Y}_{it}(0) = A'_{it}\hat{\lambda}_i + X'_{it}\hat{\delta}_t, \tag{4}$$

$$\hat{\tau}_{it} = Y_{it} - \hat{Y}_{it}(0); \tag{5}$$

3. Estimate the weighted average of these individually treatment effects τ_ω as:

$$\hat{\tau}^{\text{BJS}} = \sum \omega_{it}\hat{\tau}_{it}. \tag{6}$$

In these steps, i identifies a unique hotel-channel combination, and t denotes a month in cumulative terms. Y_{it} denotes the outcome variable of interest (in our context, $Y_{it} \in \{\ln(p_{it}) \times 100, s_{it} \times 100\}$), $Y_{it}(1)$ denotes the potential outcome that unit i at time t is treated, and $Y_{it}(0)$ denotes the potential outcome that the unit is not treated. The term $A'_{it}\lambda_i$ nests unit fixed effects, and the term $X'_{it}\delta_t$ nests time fixed effects. The term ε_{it} is the error term. We do not impose any *a priori* structure on the residuals or treatment effects. Similar assumptions as the TWFE are made, such as the uniqueness of the exogenous shock, parallel trends, and no anticipation. The coefficient of interest is τ^{BJS}, which captures the ATT of this estimator.

Matrix Completion-Nuclear Norm (Athey et al., 2021). We also employ the Matrix Completion-Nuclear Norm (MC-NN) methodology. MC-NN originates from forecasting tasks in Computer Science, and adopts Machine Learning techniques to predict the potential outcomes of treated units. Compared to the two estimators above, this method includes many other features, such as, for example, no restrictions in the matrix factorization and the regularization of the objective function through the addition of a penalty term. We note further that a version of the MC-NN estimator without regularization or factors also coincides with the DID imputation estimator (Borusyak, Jaravel and Spiess, 2023), testifying to the coherence of our methodological approach.

Like imputation estimators, MC-NN combines information on the control and treated units' pre-treatment patterns to impute the treated units' counterfactual outcomes after a given intervention. Similar to the synthetic control methods (Abadie, 2021), MC-NN synthesizes a parallel pre-treatment trend by assigning weights to only the most appropriate control units. The ATT is then calculated by subtracting the treated units' potential untreated outcomes from those realized values.

Compared to alternative methods, the advantages of the MC-NN estimator are multifaceted, enabling us to leverage the richness of our control units to the full extent. In particular, the synthetic parallel pre-treatment trend is a useful feature in the context of hotels data which, as it will become clear, are characterized by a high volatility and cyclical patterns associated to the seasonal nature of the business. In our application, MC-NN proves to be the most successful method in smoothing out such a cyclical component.

The main specification follows the form:

$$\mathbf{Y} = \mathbf{L}^* + \Gamma^* \mathbf{1}_T^\top + \mathbf{1}_N (\Delta^*)^\top + \boldsymbol{\varepsilon}, \tag{7}$$

where $\mathbf{Y}$ denote $\mathbf{Y} \in \{\mathbf{p}, \mathbf{s}\}$, the complete outcome matrices of the two outcome variables. These matrices features both the observed outcomes and the counterfactual ones. $\mathbf{L}^*$ denotes the low-rank $N \times T$ matrix of counterfactuals that we estimate. $\Gamma^* \in \mathbb{R}^{N \times 1}$ represents the hotel fixed effect, and $\Delta^* \in \mathbb{R}^{T \times 1}$ denotes the time fixed effect. Finally, $\boldsymbol{\varepsilon}$ is an error vector.

5 The Price Effects of Prohibiting PPCs in France

The estimated TWFE coefficients are reported in Table 2, Panel A. Columns (1) to (2) report the estimated price effects of the Macron Law for the two online channels, OTA and WEB, respectively. Recall that the prices for these two channels are posted on their respective websites, hence visible to everyone, including viewers and web scrapers. The TWFE coefficient (τ^{TWFE}) indicates a -1.680% change in room prices on OTAs after the prohibition of PPCs. The estimated coefficient for hotel websites (WEB) suggests a difference of -2.004%. Both coefficients, however, are not significantly different from zero.

Column (3) shows the estimated price effects for INN, the direct offline channel. As discussed above, the transactions for this channel occur offline, through emails, phone calls, and walk-in reservations. Hence, the prices for these channels are usually non-visible to nonparticipating viewers. The TWFE coefficient indicates a difference of -5.656% for INN, which translates into approximately 8.5 euros per booking in France. Compared to the online channels, the offline channel experienced a much larger price decrease, which is statistically significant from zero. Column (4), finally, also reports the overall effects of the Macron Law on French hotel prices, estimated using data from all sales channels. The resulting coefficient τ^{TWFE} indicates a -3.490% overall price effect, which is, however, not significantly different from zero.

In Table 2, Panel B, we perform the same estimations using the DID Imputation methodology developed by Borusyak, Jaravel and Spiess (2023). In Panel C, the estimations are performed using MC-NN by Athey et al. (2021). The results qualitatively confirm those obtained using TWFE, in Panel A. We also note that the estimated coefficients of all three panels are quite similar, vouching for the robustness of our results. As MC-NN offers a more flexible weighting of the control units when synthesizing the counterfactual trend, we adopt MC-NN as the estimation technique for subsequent robustness checks and heterogeneity analyses.

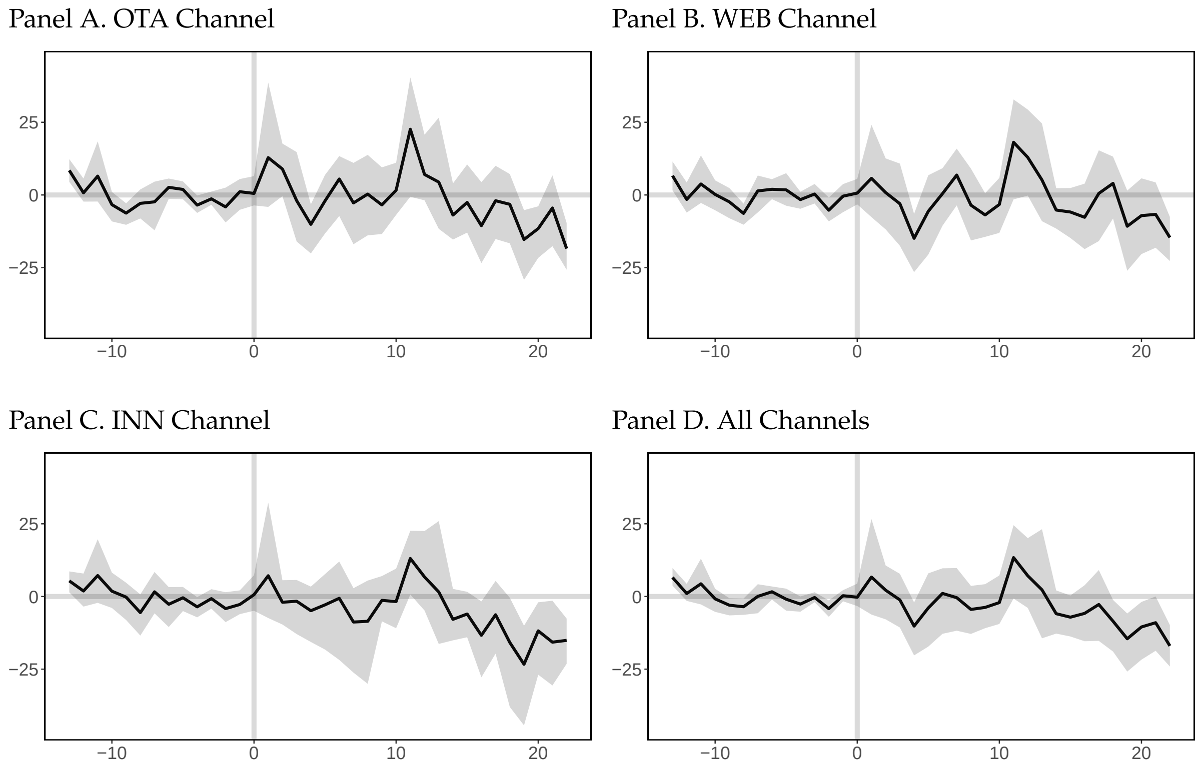


Figure 2: MC-NN Analysis of Log Price — France and Counterfactual France

To offer visual evidence that the parallel pre-trends assumption is satisfied for our analyses, we present the estimated dynamic ATTs. These are obtained by estimating (2) using MC-NN, and the results are plotted in Figure 2. For each graph, the vertical axis plots the percentage price changes, while the horizontal axis plots the number of months (36 in total) relative to the Macron Law (Month 15). The vertical bar at Relative Month 0 indicates the Macron Law. Panels A to D plot the percentage price differences of French hotels versus counterfactual French hotels, synthesized using data from hotels in the control countries. Examining the trend of percentage price differences before the promulgation of the Macron Law, we note that the pre-trends are relatively smooth and, with minor exceptions, not significantly different from zero. This suggests satisfactory pre-treatment parallel trends and attests to the suitability of our chosen control group and empirical strategies, particularly considering the span and diversity of our sample. We also present similar event study plots estimated using the TWFE specifications in Appendix C, which are similar to Figure 2 but more volatile due to the uniform weighting of control units.

Our first findings reveal an interesting picture. As noted above, the majority of policymakers and researchers suggested that a significant price decrease should follow the prohibition of all PPCs, particularly on the direct online channel. This prediction does not seem to fully hold when

Table 2—Effects of Prohibiting PPCs: Prices

	Dependent Variable: Log Price × 100			
	OTA	WEB	INN	All
	(1)	(2)	(3)	(4)
Panel A. TWFE-DID Estimates				
τ^{TWFE}	−1.680	−2.004	−5.656	−3.490
	(2.513)	(2.383)	(2.105)	(1.990)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Sales Share	17.7%	17.0%	45.9%	100%
Observations	5,406	5,418	5,302	29,175
No. of Hotels	157	157	156	157
Panel B. BJS-DID Estimates				
τ^{BJS}	−1.662	−1.956	−5.615	−3.468
	(2.476)	(2.337)	(2.069)	(1.950)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Sales Share	17.7%	17.0%	45.9%	100%
Observations	5,406	5,418	5,302	29,175
No. of Hotels	157	157	156	157
Panel C. MC-NN Estimates				
$\tau^{\text{MC-NN}}$	−1.384	−1.780	−5.343	−3.235
	(2.659)	(2.439)	(2.090)	(1.961)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Sales Share	17.7%	17.0%	45.9%	100%
Observations	5,406	5,418	5,302	29,175
No. of Hotels	157	157	156	157

Note: This table reports the estimated price effects of prohibiting PPCs. The OTA, WEB, INN column headers indicate the coefficients estimated using subsets of the data from those channels, respectively. The last column reports the estimated coefficients using data from all sales channels. Panel A reports the TWFE results estimated using Equations (1). Panel B reports the DID coefficients estimated using Equations (3) to (6). Panel C reports the MC-NN estimates using Equation (7). Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times.

we use our sample to analyze the Macron Law, the very first intervention in the EU. Indeed, as expected and consistent with our Theoretical Prediction 1, prices have decreased following the prohibition of all PPCs. This is revealed by all the negative signs in Table 2. Further, the prices of hotel rooms decreased more on the direct online channel than on OTAs. However, the difference is not statistically significant, and, importantly, neither coefficient is significantly different from zero. As a result, Theoretical Prediction 1 is only partially confirmed. Nevertheless, the results indicate a significant price decrease on the main non-visible offline channel. These findings seem to support Theoretical Prediction 2 and suggest that, following the Macron Law, hotels in France have offered better deals to customers reserving through the non-visible offline channel.

Robustness. We move beyond the baseline analysis and assess the robustness of our main findings in several directions. First, as the Macron Law was approved by the French Parliament between June and July 2015, we consider the possibility of anticipatory and lagged effects in Online Appendix D. Panels A and B of Table D.1 present the estimated coefficients using MC-NN when we shift the treatment period one month before or after the Macron Law. This accounts for OTAs and hotels' possible anticipation of the policy and the gap between room reservations and check-in. The results are qualitatively and quantitatively similar to our main findings.

If anything, our results suggest that the Macron Law was not anticipated, and its effects may be lagged, as the estimated coefficients become slightly more pronounced as we shift the treatment period later. This view is consistent with the notion that prices may take some time to adjust, for example, because hotels usually renegotiate their deals with OTAs once a year. This perspective is supported by examining the evolution of OTA commission rates faced by two of the hotel groups in our sample, which we analyze in more detail in Section 6 and Appendix F. That evidence suggests that changes in commission rates occur periodically, usually around the end of each fiscal year. It is then plausible to infer that online hotel prices may have also exhibited a lagged response to the Macron Law, given that prices partially reflect the commission rates paid to the OTAs (Wang and Wright, 2020).

Finally, in Online Appendix E, we extend our baseline analysis by including the observations from hotels in Paris, a city that was subject to a severe terrorist attack in November 2015, as we previously anticipated. The inclusion of these observations leaves the main findings qualitatively unaffected, but it affects the magnitude of the effects compared to Table 2. Indeed, the estimates presented in Table E.1 suggest that the negative price changes are not statistically significant on the OTA and WEB channels (columns 1 and 2), whereas they are on the hotel offline direct channel, INN (column 3). All the coefficients, including the one for all channels (column 4), are larger in magnitude compared to our baseline.

6 Mechanisms and Heterogeneity

Our analysis so far has established that prohibiting PPCs has a negative effect on the prices of hotels in France on the OTA channel and their websites (WEB). The effects are, however, of limited magnitude and not statistically significant across all our specifications. A more substantial and statistically significant effect is instead detected on the main offline channel (INN). In order to gain further insights into these effects and what mechanisms are driving them, we proceed as follows. First, we study whether the prohibition of PPCs also had an impact on the usage of each sales channel, as measured by the share of rooms that are sold through each of the channels. Second, we make use of the partial and limited information on OTA commission rates, to relate their changes to price movements following the Macron Law. Finally, we consider both the pre-treatment reliance of a hotel on OTAs and the pre-treatment occupancy as possible important moderating factors of the price impact of prohibiting PPCs.

Effects of Prohibiting PPCs on Channel Shares. We now examine the effects of the Macron Law on the sales share of each channel. The sales share of a reservation channel is calculated as the room nights sold through that channel divided by the total room nights sold by the hotel in a given month. Compared to alternative variables (such as room nights), channel share is presented as a percentage and, hence, is already normalized across hotels and across countries. At the same time, it is directly proportional to the number of room nights booked through a specific sales channel.

Table 3—Effects of Prohibiting PPCs: Channel Shares

	Dependent Variable: Channel Share × 100		
	OTA (1)	WEB (2)	INN (3)
Panel A. TWFE-DID Estimates			
τ^{TWFE}	−2.121	−0.864	4.526
	(0.836)	(0.712)	(1.107)
Months FE	✓	✓	✓
Hotels FE	✓	✓	✓
Observations	5,406	5,418	5,302
Panel B. BJS-DID Estimates			
τ^{BJS}	−2.120	−0.839	4.509
	(0.814)	(0.672)	(1.080)
Months FE	✓	✓	✓
Hotels FE	✓	✓	✓
Observations	5,406	5,418	5,302
Panel C. MC-NN Estimates			
$\tau^{\text{MC-NN}}$	−2.149	−0.890	4.600
	(0.850)	(0.742)	(1.079)
Months FE	✓	✓	✓
Hotels FE	✓	✓	✓
Observations	5,406	5,418	5,302

Note: This table reports the estimated effects of prohibiting PPCs on channel shares. The OTA, WEB, INN column headers indicate the coefficients estimated using subsets of the data from those channels, respectively. Panel A reports the TWFE results estimated using Equations (1). Panel B reports the DID coefficients estimated using Equations (3) to (6). Panel C reports the MC-NN estimates using Equation (7). Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times.

Studying the changes in channel shares allows us to examine whether the hotels in our sample experienced a rebalance in the transactions through their various reservation channels after the enactment of the Macron Law. Additionally, we can assess whether there were shifts in sales across different channels. Table 3, Panel A to C report the estimated coefficients for the three empirical methods employed in our paper.

Columns (1) to (2) report the estimated effects of the Macron Law on channel shares for the visible online channels, OTA and WEB. The TWFE coefficient (τ^{TWFE}) indicates a -2.121% and statistically significant change in the share of sales finalised through OTAs after the Macron Law. This corresponds to approximately 10 room nights per month for a typical hotel in our sample. On the other hand, the estimated coefficient for hotel websites (WEB) is of lower magnitude, -0.864%, and not statistically different from zero.

Interestingly, whereas we did not find statistically significant price decreases on either of these channels, there was a relative decrease in the number of transactions finalised through OTAs. If one were to analyse the price effects of the legislation in isolation, these effects on sales shares would be neglected, and, as a result, the overall effects of the policy may be misestimated. These findings indicate that, following the implementation of the Macron Law, there was a decrease in the number of bookings finalized through OTAs for French hotels compared to those in the control countries. In contrast, reservations made through the hotels' websites also decreased but in a lower and not statistically significant proportion.

Column (3) reports the estimated effects on the sale shares of the non-visible INN channel. Compared to the visible online channels, information regarding the quantities (such as the number of available rooms) of the direct offline channel cannot be directly observed or retrieved by web scraping. Nonetheless, this data constitutes a substantial share of the total room nights sold by hotels, averaging above 40%.[5] As a result, a thorough analysis of the dynamics of INN is crucial for accurately assessing the impact of the legislation on hotels.

The TWFE coefficient indicates a significant increase of 4.526% after the Macron Law was enacted, or about 61 room nights per month, relative to the control. This substantial increase in the sales share of the main offline channel contrasts the significant decrease in the OTA channel, and indicates that a portion of the room nights sold has shifted from online platforms (OTA) to offline direct bookings (INN). We note that also, in this case, the estimated coefficients are quantitatively similar across Panel A to Panel C, vouching for the robustness of our results.

Finally, Figure 3 presents the estimated dynamic ATTs. The interpretation of each graph is similar to the graphs in Figure 2 with the difference that sales shares, rather than percentage prices, are presented on the vertical axis. These figures offer visual evidence that the parallel pre-trends assumption is also satisfied for our sales share analyses. Indeed, as for the price analyses, the pre-trends are relatively smooth and, with minor exceptions, not significantly different from zero. The post-Macron Law patterns graphically showcase the results discussed above: a significant sales shift from the OTA channel to INN. It is also noticeable that this shift took a few months to materialize. Indeed, sales shares in both OTA and INN did not change significantly in the immediate months after the prohibition of PPCs.

Overall, the following picture emerges. Examining the price and sales effects holistically, we

[5]See Appendix B for further information on sales shares by channel.

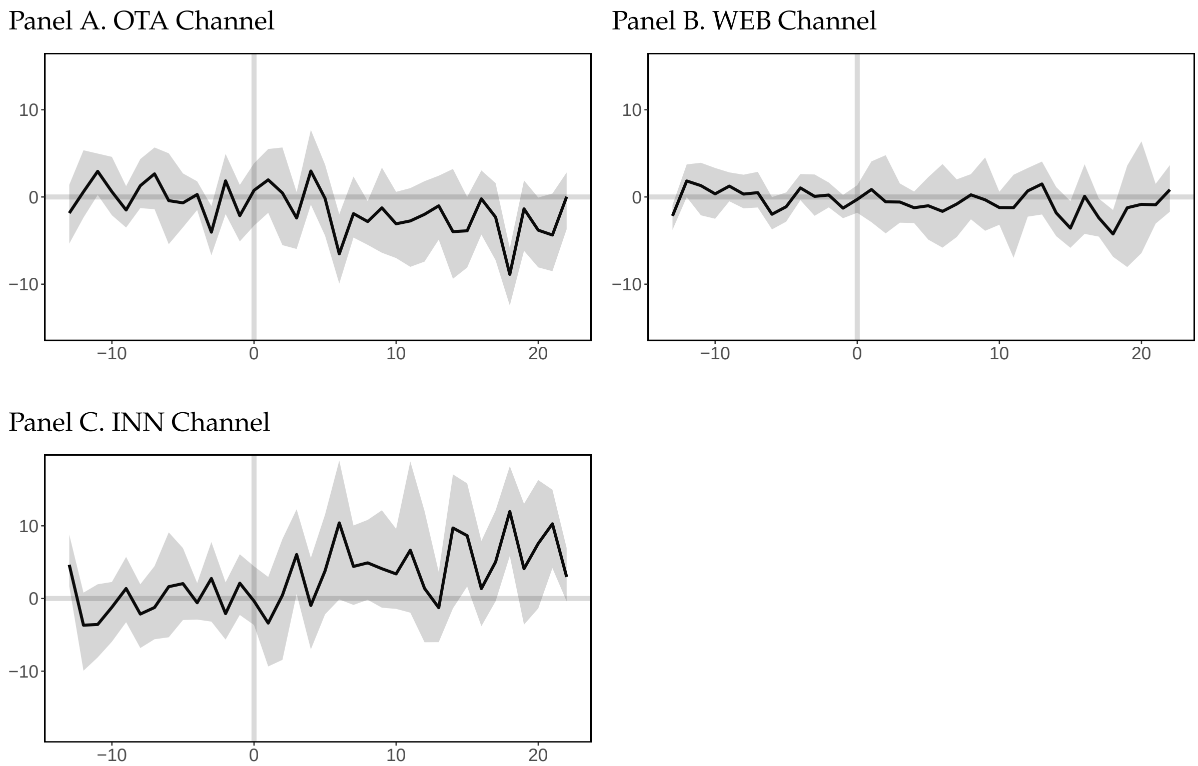


Figure 3: MC-NN Analysis of Channel Shares — France and Counterfactual France

document a non-significant price change on online channels such as the OTAs and hotels' official website, but also a significant sales shift from the OTAs to the hotels' main offline channel, INN, where price has decreased significantly. These findings suggest that, while the hotels seemed hesitant to decrease their room prices displayed on online channels (that is, it is likely that they still mostly respected the price parity between OTAs and their official website), it is possible that they focused on raising consumer attention on the offline booking channels and offered better deals for direct offline reservations. Indeed, anecdotal evidence suggests that hotels have started marketing their direct channels more aggressively in the same period (HOTREC, 2015; Gonzalo, 2016). Hence, this may have led to a subset of consumers searching for better booking deals and switching to the offline channel.

We note that these changes occurred in a period characterized by a general expansion of the usage of OTAs and a progressive decrease in the share of transactions taking place through the offline direct channel. The prohibition of PPCs seemed to have slowed down these trends for both channels in France with respect to the control countries. It is important to note that, although we document a share of consumers switching from OTAs to the offline channel, we did not register an expansion in the overall number of room nights in France. Indeed, the average number of room nights reserved through OTAs in France increased less than that of the control (on average, 39 more room nights *vis à vis* 49 for the control), and they decreased less on the main offline channel (on average, 64 fewer room nights *vis à vis* 137).

Price Effects and Commission Rates Reductions. Our discussion of possible lagged price effects of the Macron Law in Section 5 hinted at a relation between the price changes and the evolution of the commission rates. In this section, we delve deeper into the relationship between prices and OTA commission rates. We will do this by focusing on Hotel Group 1, which provided us with granular data on the OTA commission rates for each establishment affiliated with it.[6]

Figure 4: Normalised OTA Commission Rates: Group 1

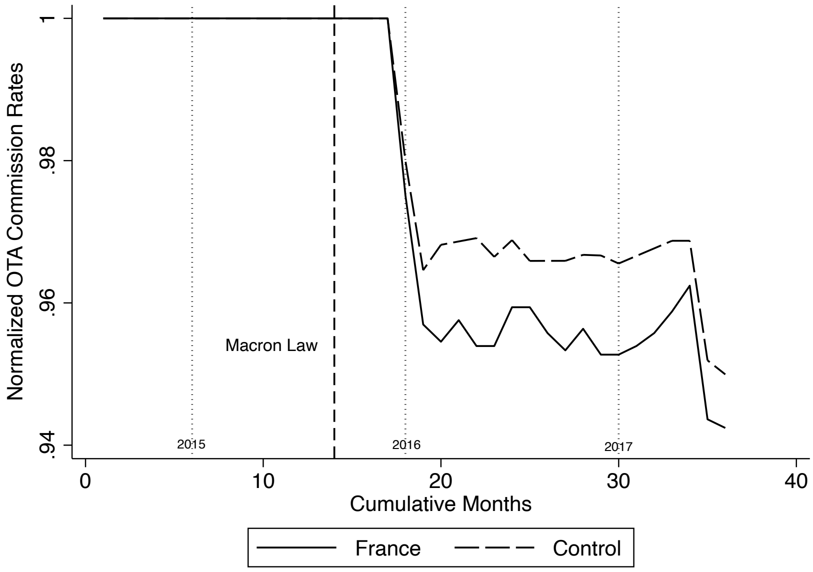


Figure 4 reports the time series of the normalized OTA commission rates for establishments belonging to Hotel Group 1 in France and in the control group, respectively. It can be observed that, several months after the Macron Law, there was an approximate 4% reduction in the OTA commission rates faced by the hotels in this group. This change occurred at the start of 2016, and it was most likely the result of renegotiation between the hotel group and the OTAs. A similar but less intense reduction can be observed in 2017, closer to the end of our sample period. It is also worth noticing that the commission rate change is not identical for the hotels in the treated and the control group: indeed, the French hotels enjoyed a 1.013% further reduction in 2016 (approximately -4.444%) than their sister hotels operating in the control countries (approximately -3.431%).

In light of the decrease in the rates in 2016 and the relative difference between treated and control hotels, we now perform the MC-NN analysis only on hotels belonging to Hotel Group 1. The estimated coefficients are reported in Table 4 and the estimated dynamic ATT plots in Appendix G. Although this exercise is only performed on a reduced sub-sample of hotels, the pre-trends of the ATT plots are sufficiently smooth, with no noticeable deviations from zero. Focusing on the effects of the prohibition of PPCs, we can start from Table 4, Column (1). To begin with, one may notice that the reduction of OTA prices for Hotel Group 1 (-1.309%) is in line with the one for the full sample in Table 2, Column (1). Indeed, the two estimates are not significantly different (t-statistic = 1.1985). Second, as in our baseline model with all hotels, the price decrease on the OTA channel is not statistically different from zero. Further and more interestingly, the estimated relative prices of French hotels seem to have decreased by an amount slightly larger but in line with that of the relative reduction in the OTA commission rates. As

[6]Hotel Group 2 also provided information about commission rates, but at a more aggregate level. That evidence can be found in Appendix F, Figure F.1.

a matter of fact, the estimated coefficient is statistically different from -1.013% (t-statistic = -6.7668), i.e., the approximate relative change in the OTA commission rates discussed above.

Table 4—Price Effects: Hotel Group 1

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. Hotel Group 1				
$\tau^{\text{MC-NN}}$	-1.309	-2.372	-6.016	-3.828
	(2.091)	(2.522)	(2.370)	(1.556)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	2,285	2,296	2,304	12,316
No. of Hotels	64	64	64	64

Note: This table reports the estimated price effects of the Macron Law on hotels that belong to Hotel Group 1. The analyses are performed using the MC-NN estimator. The WEB, OTA, INN column headers indicate the coefficients estimated using subsets of data from the respective channels. The last column reports the estimated coefficients using data from all sales channels. Panel A reports the MC-NN estimates using Equation (7). Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times.

Taken together, these insights suggest that, despite the bargaining power of this internationally renowned hotel group, when experiencing a legislative ban on PPCs, its establishments lower prices only in proportion to the reductions in the OTA commission rates. In other words, there was little or no *between-channel* pro-competitive effect of removing PPCs from OTAs. Any detected effect, with the due caution of not being statistically significant, seems to be at most related to the pass-through of a lower OTA commission fee.

Table 4, columns (2) to (4) presents the estimated price effects of the Macron Law on hotels belonging to Hotel Group 1 for the WEB, INN and All channels, respectively. The estimated coefficient for WEB is not statistically significant, which is qualitatively similar to the results of the overall analyses in Table 2, column (2). The coefficient on INN in column (3) is -6.016%, which is statistically significant and greater in magnitude than the baseline coefficient (Table 2, Column 3), suggesting that the results from Hotel Group 1 were important contributors to the negative and significant price effect estimated for the INN channel. Finally, the price reduction of the sales channels taken together (column 4) is in line in terms of magnitude with the baseline in Table 2, Column (4).

Heterogeneity by Pre-Treatment OTA Reliance. The mechanisms behind the price effects of the Macron Law can be better understood by looking at the heterogeneous treatment effects. For example, a moderating factor that may drive price changes could be the hotels' relative reliance on OTAs. HOTREC (2020) showed that between 2013 and 2019, online travel intermediaries' market share has steadily increased in the European hotel sector from 19.7% in 2013 to 29.9% in 2019. Table 2 shows that the average share of sales for the hotels in our sample was 17.7%, below the European average of our period of study. There is, however, heterogeneity between hotels with regard to this share. Focusing only on the period before the implementation of the Macron

Law, the mean of the sales share on OTAs was 19.2%, with an 11.9% standard deviation.

On this basis, we define hotels with a relatively high reliance as those whose OTA sales accounted for more than 20% of their total sales prior to the Macron Law. The reasoning is that hotels that rely less on OTAs may be more capable of taking advantage of the higher price flexibility that the prohibition of PPCs provides them with. On the contrary, hotels whose sales are comparatively more dependent on OTAs would be less willing to charge prices that would violate PPCs, even when they are no longer legally enforced, to minimise the risk of a negative impact on their visibility and efficacy on the platforms.

The hotels are then split into two categories according to the above introduced *pre-treatment* reliance on OTAs, and we examine the heterogeneous responses of hotels within these different categories. To address the issue of reduced power due to subsetting the data, we perform this analysis using the MC-NN estimator and allow pre-treatment observations from the entire set of control hotels (regardless of their pre-treatment OTA dependence) to be used as candidates for imputing the post-treatment counterfactual.

Table 5—Heterogeneous Effects: Pre-Treatment OTA Reliance

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. OTA Share Less Than 20%				
$\tau^{\text{MC-NN}}$	−1.748	−1.893	−6.948	−3.704
	(3.644)	(3.065)	(2.756)	(2.355)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,276	5,288	5,172	28,486
No. of Hotels	156	156	155	156
Panel B. OTA Share Greater Than 20%				
$\tau^{\text{MC-NN}}$	−0.861	−1.704	−2.858	−2.506
	(2.451)	(2.715)	(1.745)	(1.691)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,232	5,244	5,128	28,215
No. of Hotels	157	157	156	157

Note: This table reports the estimated heterogeneous price effects of the Macron Law using two subsets of the sample. The hotels are split into two categories according to their *pre-treatment* dependence on OTAs. The analyses are performed using the MC-NN estimator following Equation (7). The WEB, OTA, INN column headers indicate the coefficients estimated using subsets of data from the respective channels. The last column reports the estimated coefficients using data from all sales channels. Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times.

This approach has a number of advantages. If the potential control group was limited to hotels with the same sales share of the OTA channel, the potential cross-country differences could lead to losing a number of potential valid donors for the counterfactual. In other words, the evolution of prices for hotels in different countries might be similar, even if they do not have the same level of OTA dependence. As the MC-NN estimator optimally synthesizes the untreated counterfactual by leveraging the available pre-treatment observations, this procedure allows us to utilize more of the sample and, at the same time, reduces the risk of excluding useful information that can contribute to creating more stable pre-trends. The trend plots of this analysis can be found in Appendix H. It can be noted that the pre-trends are satisfactorily stable.

Table 5, Panel A reports the estimated price effects of the Macron Law for hotels with a pre-treatment OTA share of less than 20%, and Panel B, those with more than 20%. In other words, Panel A analyses the price effects of French hotels that were less reliant on OTAs in their sales before the Macron Law. Overall, we note that the magnitude of the price reductions for each booking channel is greater in Panel A than in Panel B. This difference is especially pronounced in Column (3) for the offline direct channel, INN, where we document a statistically significant price decrease of -6.948% in Panel A, but a non-significant coefficient of -2.858% in Panel B. Such a decrease in INN is also significantly larger than the one in the baseline in Table 2, Panel C (t-statistic = -33.52). Generally, Panel B shows that the hotels that were *ex-ante* more reliant on OTAs decreased their prices for the three main booking channels less than their less reliant counterparts (Panel A), and none of their decreases is statistically significant.

These findings are consistent with our expectations: hotels that were *ex-ante* more reliant on OTAs for their sales are also likely to be more concerned about the potential (implicit or explicit) penalties occurring if they stop respecting price parities on OTAs. At the same time, hotels which were *ex-ante* less reliant on OTAs would also be less affected by any ranking or algorithmic changes that may occur or may be imposed by OTAs following a differential pricing strategy on different sales channels.

Heterogeneity by Pre-Treatment Occupancy Rate. Next, we examine the heterogeneous responses of hotels with different occupancy rates. Occupancy can act as a moderating factor as hotels with a relatively high occupancy may be more resilient to shocks coming from any particular booking channel. Hence, they may be more keen on experimenting and differentiating prices on different channels once PPCs cannot be legally applied. Provided that occupancy is not always close to 100%, this can be consistent with offering lower rates or discounts to customers on a particular channel.

We note that the average occupancy rate of hotels in our dataset is quite high compared to that of Europe. According to Eurostat (2024), the average occupancy rate of bedrooms in hotels and similar accommodations in Europe was only around 54.3% in 2014 and 57.3% in 2015. The occupancy in the hotels in our sample before the implementation of the Macron Law was on average 66.2%, with a standard deviation of 15.8%.

For this analysis, we split the hotels into two categories according to their *pre-treatment* occupancy: those with a pre-treatment occupancy rate of less than 65%, the approximate average for the hotels in our sample, and with a pre-treatment occupancy rate of less than that threshold. To address the issue of reduced power and account for potential cross-country heterogeneity in occupancy levels, we again allow control units from the entire sample to be used as candidates for synthesizing the untreated counterfactual. We present the estimated ATT plots of this analysis in Appendix I. It can be noted that, also in this case, the pre-trends are satisfactorily stable.

The results are in Table 6. Panel A reports the estimated price effects of the Macron Law for hotels with a pre-treatment occupancy rate of less than 65%, the approximate average for the hotels in our sample. Panel B reports the estimated coefficients for hotels with more than 65% pre-treatment occupancy rate. Overall, the magnitude of the price reductions for each booking channel is smaller in Panel A than in Panel B. From Columns (1) to (3), one can note that this difference is pronounced and amounts to several percentage points for every channel. In particular, the -4.635% price reduction of channel INN for hotels with relatively lower occupancy is statistically significant, the only one in Panel A. The price reductions in Panel B, however, are statistically different from zero for each channel, ranging from -3.870% on WEB to -4.927% on OTA, and to a pronounced -7.772% on INN. Overall, the prices of hotels with a relatively high occupancy rate experienced a significant reduction of -5.385%. All of these effects are significantly larger (in absolute value) than the ones reported in the baseline, Table 2, Panel C (t-statistics are -52.83, -72.04, -45.09 and -42.95, respectively).

Table 6—Heterogeneous Effects: Pre-Treatment Occupancy Rates

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. Occupancy Less Than 65%				
$\tau^{\text{MC-NN}}$	−0.338	−1.199	−4.635	−2.537
	(3.177)	(2.864)	(2.404)	(2.352)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,320	5,332	5,216	28,698
No. of Hotels	156	156	155	156
Panel B. Occupancy More Than 65%				
$\tau^{\text{MC-NN}}$	−4.927	−3.870	−7.772	−5.385
	(2.401)	(1.559)	(3.250)	(1.784)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,188	5,200	5,084	28,003
No. of Hotels	157	157	156	157

Note: This table reports the estimated heterogeneous price effects of the Macron Law using two subsets of the sample. The hotels are split into two categories according to their *pre-treatment* occupancy rate. The analyses are performed using the MC-NN estimator following Equation (7). The WEB, OTA, INN column headers indicate the coefficients estimated using subsets of data from the respective channels. The last column reports the estimated coefficients using data from all sales channels. Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times.

Once again, these findings are in line with our initial expectations. Indeed, hotels with relatively high occupancy rates are less exposed to booking channel shocks, such as it could be an eventual "dimming" of their search ranking on OTAs. Their counterparts with relatively low occupancy rates would instead be more likely to be hurt by reduced visibility on online platforms. On the one hand, our findings suggest that the French hotels of the latter category (Panel A), even without a formal contractual obligation to maintain price parities, were hesitant to decrease their prices on the visible online channels, perhaps due to concerns that their occupancy rates would be further affected. On the other hand, the French hotels of Panel B, which enjoyed an *ex-ante* relatively high occupancy, leveraged the prohibition of all types of PPCs and reduced their prices in a way which could attract more customers to their direct offline channels, for which they do not have to pay a commission fee per reservation.

7 Implications for Consumer Welfare

We now ask the following two questions. First, how generalizable are the results presented so far? Second, can we gauge the magnitude of the estimated effects on the welfare of consumers in France and, if so, under what assumptions? These questions are relevant due to the diverse nature of establishments owned by the international hotel groups of our study, which may differ significantly from those found elsewhere in France and in other European countries.

Fortunately, we can combine our sample with data on the population of French and European hotels between 2014 and 2017, and rely on these external data sources to calibrate the characteristics of our hotels to those that match the population of French hotels. However, the following results regarding the potential impact on consumer welfare should be considered as a thought experiment, as we cannot definitively assert that the effects we estimate can be applied to all hotels in France.

Under the above caveat, we adopt two approaches to estimate the consumer surplus implications of the Macron Law. The first one is based on the methodology proposed by Kang and Vasserman (2022) and calculates robust bounds for changes in consumer surplus by providing estimates for demand functions of different families. The second one leverages the estimated ATT of our study and approximates the overall changes in consumer surplus by incorporating data on monthly room nights sales of French hotels of different star ratings. We note that these methods do not require any equilibrium assumptions on firms' behavior or optimal pricing, as would be the case in a structural approach (Canzian et al., 2021). More details regarding the external data and these methodologies can be found in Appendix J.

We focus our consumer welfare analysis on the direct offline channel, INN, as it is the one where we consistently observe significant changes in both prices and sales shares. Also notice that the estimated relative effects for INN were much larger in magnitude than the online channels (as shown in Table 2). Given that the sales share of INN is approximately the same as the two online channels combined, the overall magnitude for the latter channels would also likely be smaller. As a result, by focusing only on the INN channel, we provide a lower bound for the consumers' gains. Furthermore, as we found no significant price effects on the OTA and WEB channels, we cannot rule out the possibility that the relative price changes induced by the Macron Law on these channels were zero.

Finally, as our hotels are categorized as 3-star or above, we limit our analysis to French hotels of the same rating. This is a limitation of our approach, but, at the same time, it is likely that the relative gains in consumer surplus for hotels with few star ratings are much smaller, as hotels with one or two stars ought to have an even higher reliance on OTAs.

For the first approach, we leverage the fact that our dataset contains information about prices and quantities (room nights) and use the subscripts 0 and 1 to denote the value of price (p_0 and p_1) and room nights (q_0 and q_1) before and after the Macron Law. Following Kang and Vasserman (2022), we estimate the robust bounds for the changes in consumer surplus (Δ CS) of the Macron Law on hotels in our sample. This implies assuming that the functional form of the demand function is convex but still satisfies Marshall's second law, according to which the price elasticity of demand for hotel rooms is increasing in the price.

Given such assumptions, the lower bound of Δ CS is obtained for a demand function with constant elasticity of substitution (CES), which offers the robust lower bound for Δ CS of demand functions between (p_0,q_0) and (p_1, q_1):

$$\Delta \text{CS}_{\text{CES}} = \frac{(p_0 q_0 - p_1 q_1)\log(p_0/p_1)}{\log(p_0/p_1) + \log(q_0/q_1)}. \tag{8}$$

The robust upper bound of Δ CS is obtained for a linear demand function:

$$\Delta \text{CS}_{\text{Linear}} = \frac{(p_0 - p_1)(q_1 + q_0)}{2}. \tag{9}$$

Note that the lower bound provided by the CES demand function may be overly conservative, as it is rare for demand functions to be so convex that they violate Marshall's second Law. Consequently, we also provide the lower bound of demand functions belonging to the family with decreasing marginal revenue (DMR), which is obtained by a demand with constant marginal revenue: For additional reference, we also calculate the conservative bounds proposed by Varian (1985), which only assumes that the demand is decreasing in prices:

$$\Delta \text{CS}_{\text{Varian}} \in [(p_0 - p_1)q_1, (p_0 - p_1)q_0]. \tag{10}$$

Table 7 presents the robust bounds for the relative changes in consumer surplus induced by the Macron Law for the direct offline channel, INN. We focus on the hotel categorization by star ratings, as it is a standard metric in the hospitality industry, and such data are available for all the French hotels of each category. The relative gains in consumer surplus are calculated up to June 2017, the end of our sampling period. The robust (CES and Linear) and conservative (Varian) bounds are calculated by first estimating the average Δ CS for hotels in our sample using equations (8) to (10), then multiplying by the number of French hotels of each star rating.[7] We account for the differences between our sample and the population by scaling the consumer welfare gains using the ratio in occupancy rates. The results are expressed in millions of euros. The overall estimates suggest that visitors of hotels in France may have saved between 180 and 216.8 millions euros in the months following the approval of the Macron Law, compared to their counterpart in other EU countries.

Our second approach is an alternative method for approximating the relative gains in consumer surplus following the Macron Law, capturing a hypothetical situation in which the effects detected for the hotels in our sample apply, at least in part, to the population.

The overall Δ CS is calculated using the estimated coefficients for the ATT obtained using the MC-NN estimator, multiplied by the total room nights, and then by the share of the direct

[7] Data source: Direction Générale des Entreprises (2022).

Table 7—Relative Gains in Consumer Surplus (France)

	Varian Lower Bound (1)	CES Lower Bound (2)	Linear Upper Bound (3)	Varian Upper Bound (4)
3-Star	70.0	79.3	79.3	88.7
4-Star	46.7	50.8	50.9	55.1
5-Star	63.3	67.9	68.1	73.0
Overall	180.0	198.0	198.3	216.8

Note: This table reports the approximated gains in consumer surplus for French hotels following the Macron Law up to June 2017. The figures are approximated using the number of French hotels in January 2017. The gains are calculated for the direct offline channel, INN, which underwent statistically significant price reductions following the Macron Law. The bounds are calculated following the procedures proposed by Kang and Vasserman (2022) and calculated using equations (8) to (10). The units are in millions of euros.

offline channel, INN. To account for the differences between our sample and the population, we scale the welfare effects by the ratio of occupancy rates, and allow for the potential differences in INN shares and the magnitudes of the ATT. Column (2) in Table 8 presents the upper bound for such approximations, calculated by only multiplying the relative price ratio and assuming all French hotels experience the same INN shares and ATT as hotels in our sample. This is undoubtedly an overestimate of Δ CS, as independent hotels rely more on online channels for their bookings, and may be more hesitant to reduce prices. To account for these differences, the lower bound of Column (1) in Table 8 is calculated by assuming that the overall population of hotels employs less of the INN channel and experiences a more moderate ATT. Specifically, we scale down the ATT by half. Note that the bounds in Table 8 are especially sensitive to the estimated values of the ATT and are, hence, more volatile than those in Table 7.

Table 8—Approximated ΔCS using ATT (France)

	Lower Bound (1)	Upper Bound (2)	Room Nights (3)
3 Stars	30.9	85.6	92.3
4 & 5 Stars	117.8	356.7	59.1
Overall	148.8	442.3	151.4

Note: This table reports the approximated gains in consumer surplus for French hotels following the Macron Law up to June 2017. The bounds are approximated using the estimated ATT obtained from the MC-NN estimator. The Upper Bounds most likely overestimates ΔCS as they are calculated by assuming that the overall population of French hotels enjoyed similar price reductions as the chain hotels in our sample. The gains are estimated for the direct offline channel, INN, which underwent statistically significant price reductions following the Macron Law. The units are in millions of euros / millions.

We observe that, apart from the 4 & 5 stars upper bound (Table 8, Column 2), the estimated range of the relative gains in consumer surplus of the two approaches is quantitatively similar which vouches for the validity of our approximations. For example, consumers who booked directly through the INN channel of the 6,000 3-star hotels in all of France saved up to 90 million euros in the 22 months following the Macron Law. Similarly, for consumers who booked the 2,000 4-star and 5-star hotels through the same channel, it is estimated that more than 120 million euros were saved, despite the higher-end hotels offering fewer room nights. These results also show that a large part of the effects of the legislation occurred for high-end hotels, which is consistent with our previous interpretations that hotels with more bargaining power are in a better position to take advantage of the policy change, with further gains for their consumers. Finally, it is worth noting that, due to the assumptions made on the ATT, the results estimated with the second method exhibit somewhat greater magnitude in the upper bound compared to those obtained using the first method based on Kang and Vasserman (2022).

8 Conclusions

In this paper, we provided a comprehensive empirical evaluation of the impact of the Macron Law, which was introduced in France in 2015 as the first-of-its-kind legislative ban on all types of price parity clauses (PPCs) in the lodging sector. We mainly focused on the price effects of this relevant policy change but also examined its impact on the redistribution of shares across different sales channels. Our analysis was based on a unique proprietary dataset of chain hotel prices spanning three years from 2014 to 2017 and including all sales channels.

Both TWFE DID and Matrix Completion-Nuclear Norm (MC-NN) analyses indicated that the prohibition of PPCs had negative but not statistically significant effects on room prices posted on OTAs or hotel websites, the visible channels. However, we identified a significant price reduction on the hotels' main offline channel. In addition, we obtained a significant decrease in the sales share of OTAs, accompanied by an increase in the offline direct channel. These results proved to be robust to a number of specifications and estimation techniques, including anticipatory reactions and lagged effects of the legislation.

Our findings are noteworthy as they reveal that the main pro-competitive effect of the policy reform did not manifest on OTAs or hotels' websites, as initially expected, but rather on the main offline channel, where information is exclusively known to the hotels and their clients. This is highly relevant as it reflects real-world consumer diversity. Especially in digital markets, research should always account for this diversity and keep track of the evolving composition of consumers. Interestingly, the estimated consumer welfare implications of the Macron Law indicated substantial savings for consumers who booked directly through the offline channel, adding a quantifiable dimension to the impact of the policy. For instance, our estimates imply significant savings for visitors to hotels in France as a result of the policy change. In terms of the whole population of French 3-star hotels, we estimated that consumers who booked directly saved up to 90 million euros in the 22 months following the implementation of the Macron Law. The range of overall savings, relative to their counterparts in the rest of the EU, amounts to hundreds of millions of euros.

The analyses of heterogeneous effects yielded further insights. Using granulated data from one of the hotel groups in our sample, we discovered that a decrease in OTA commission rates corresponded to a comparable, but not statistically significant, reduction in online prices, only partially in line with the relevant theoretical predictions (Boik and Corts, 2016; Wang and Wright, 2020; Calzada, Manna and Mantovani, 2022). However, prices on the direct offline channel saw significant reductions for the French hotels within that group, particularly those experiencing a greater decrease in OTA commission rates. Additionally, we documented heterogeneous price effects of the Macron Law, with hotels that *ex-ante* relied less on OTAs or enjoyed higher occupancy rates experiencing more pronounced price reductions.

One may wonder if significant price decreases may have been registered in other types of establishments, for example, smaller chains or independent hotels. Whereas we cannot discard this possibility, we believe it is unlikely. First, chain hotels have well-established corporate websites that can be easily found through search engines. As a result, they enjoy demand-side advantages (Hollenbeck, 2017) that render them less reliant on OTAs. Second, chains are more agile in sharing information (Baum and Ingram, 1998) and have additional managerial resources to deal with the complexities of price setting (Abrate and Viglia, 2016). These factors suggest that chain hotels are in the best position to take advantage of the price flexibility and increased competition opportunities offered by banning PPCs.

The richness of our dataset and the novelty of our methodology enabled us to go beyond the extant literature in several ways. The study of Hunold et al. (2018) was based on indirect evidence about hotels in different countries collected by the metasearch engine Kayak. Ennis, Ivaldi and Lagos (2023), similar to us, relied on actual transaction data for chain hotels operating across countries in the EU and the rest of the world. Both studies, however, focused on the probability that the direct online channel (official websites) offered the lowest price. Mantovani, Piga and Reggiani (2021) provided quasi-experimental evidence by analyzing data scraped from Booking.com. They did not, however, observe the hotels' direct sales channels. Finally, we are the first to relate the price effects to the commission rates of OTAs.

Despite the extensive dataset utilized in our analysis, certain limitations were encountered. Firstly, the OTA channel encompasses transactions completed on major platforms, such as Expedia and Booking.com, as well as smaller ones like Ctrip or Hotel.de. Unfortunately, we were unable to distinguish between OTAs, which prevented us from analyzing the differential impact of prohibiting PPCs on specific platforms. In addition, the existing literature suggests that the removal of PPCs may lead to the entry of new OTAs (Ezrachi, 2015), but could also stifle incumbent platforms' propensity to invest and innovate (Wang and Wright, 2022). Regrettably, issues related to to market entry and innovative activities carried out by OTAs fall outside the scope of this paper. Moreover, while we extrapolated our empirical findings to the population of 3-star to 5-star hotels in France, we were unable to do so for one-star and two-star hotels due to limited quantitative information on how the Macron Law would impact them.

Notwithstanding these limitations, our evidence showed that eliminating PPCs alone did not produce sizeable price reductions in the intended channels. There may be several reasons for the limited and non-significant price effects on the visible online channels for the hotels in our sample. For example, a survey in European Competition Network (2017) has documented a scarce awareness of hoteliers regarding these policy changes. About half of them did not know that OTAs had changed their parity clauses in the previous year. This explanation may not hold in our scenario, given that we consider chain hotels belonging to large international groups whose management is likely to be well-informed about the latest developments in the sector.

More coherent with our setting, and in general with our analyses of the sector, is the consideration that OTAs seem to have elaborated a set of strategies that achieved similar outcomes as PPCs. On the one hand, retaliatory practices, such as the previously explained "dimming" (Hunold, Kesler and Laitenberger, 2020), acted as a deterrent for price differentiation by hotels. In fact, OTAs kept monitoring the hotel pricing strategies through rate checker software and contacted them regarding eventual parity violations (anecdotal examples are provided in

Appendix K). On the other hand, platforms reinforced collaboration ties with those hotels that respect their provisions, rewarding them with better listings, enhanced services, and recommendation systems that serve such purpose (Peitz, 2022; Scott Morton, 2023). Taken together, these strategies could represent an effective way to circumvent the ban on PPCs. At the same time, our analysis suggests that platform clients were partly successful in redirecting some of their demand towards non-visible offline channels, which are less subject to platforms' direct control.

In order to level the playing field between dominant platforms and sellers resorting to their services, recent contributions suggested the imposition of measures such as capping commission rates (Gomes and Mantovani, 2024; Tirole and Bisceglia, 2023; Wang and Wright, 2023) and curbing recommendation biases (de Cornière and Taylor, 2019; Teh and Wright, 2020). These additional provisions are likely to play a complementary role in the design of platform regulation to ensure that the benefits of digitization are fairly distributed and shared across all stakeholders.

Our findings have relevant policy implications not only for the lodging sector but also for other sectors in which similar practices apply. The European Commission, for example, recently investigated Amazon for removing the Buy Box feature for those sellers that charge lower prices on different online channels (Commission Case AT.40703 Amazon Buy Box).[8] In the US, the legal battle brought by Epic Games against Apple's mandatory payment system did not achieve the goal of allowing direct selling but resulted in prohibiting Apple from imposing "anti-steering provisions," which limited the sellers' ability to inform consumers of alternative sales channels.[9] In the EU, the DMA already addresses practices that serve as substitutes to PPCs,[10] and exclusivity requirements.[11] Our paper suggests that policymakers and antitrust authorities should anticipate the possible response of dominant platforms when adopting policy changes aimed at curbing the use of anti-competitive practices. Failing to do so may result in a plethora of interventions, which require consistent resources and efforts, without achieving their policy goals.

[8]In December 2022, the Commission accepted commitments by Amazon to treat all sellers equally when ranking the offers for the purposes of the selection of the Buy Box winner (see European Commission, 2022 for more details).

[9]In March 2024, the European Commission fined Apple over 1.8 billion euros for anti-steering provisions that prevented app developers from informing iOS users about cheaper music subscription services available outside the App Store (see European Commission, 2024 for more details).

[10]Recital 37 ends with "… it should not be accepted that gatekeepers limit business users from choosing to differentiate commercial conditions, including price. Such a restriction should apply to any measure with equivalent effects, such as, for example, increased commission rates or de-listing of the offers of business users."

[11]These rules apply to online intermediation Core Platforms Services. As of April 2024, the designated gatekeepers for this type of services are: Amazon Marketplace, Apple App Store, Meta Marketplace, Google Play and Google Shopping.

References

Abadie, Alberto. 2021. "Using synthetic controls: feasibility, data requirements, and methodological aspects." *Journal of Economic Literature*, 59(2): 391–425.

Abrate, Graziano, and Giampaolo Viglia. 2016. "Strategic and tactical price decisions in hotel revenue management." *Tourism Management*, 55: 123–132.

Angrist, Joshua, and Jörn-Steffen Pischke. 2008. *Mostly harmless econometrics: An empiricist's companion.* Princeton University Press.

Athey, Susan, Mohsen Bayati, Nikolay Doudchenko, Guido Imbens, and Khashayar Khosravi. 2021. "Matrix completion methods for causal panel data models." *Journal of the American Statistical Association*, 116(536): 1716–1730.

Baker, Jonathan, and Fiona Scott Morton. 2018. "Antitrust enforcement against platform MFNs." *Yale Law Journal*, 33(1): 2176–2202.

Baum, Joel, and Paul Ingram. 1998. "Survival-enhancing learning in the Manhattan hotel industry, 1898–1980." *Management Science*, 44(7): 996–1016.

Benzell, Seth, and Avinash Collis. 2022. "Regulating digital platform monopolies: The case of facebook." *SSRN Working Paper 3619535*.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How much should we trust differences-in-differences estimates?" *Quarterly Journal of Economics*, 119(1): 249–275.

Boik, Andre, and Kenneth Corts. 2016. "The effects of platform most-favored-nation clauses on competition and entry." *Journal of Law and Economics*, 59(1): 105–134.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2023. "Revisiting event study designs: Robust and efficient estimation." *Review of Economic Studies*, forthcoming.

Bundeskartellamt. 2020. "The effects of narrow price parity clauses on online sales – Investigation results from the Bundeskartellamt's Booking proceeding." *Competition and Consumer Protection in the Digital Economy*.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics*, 225(2): 200–230.

Calzada, Joan, Ester Manna, and Andrea Mantovani. 2022. "Platform price parity clauses and market segmentation." *Journal of Economics & Management Strategy*, 31(3): 609–637.

Canzian, Giulia, Gianluca Mazzarella, Louis Ranchail, Frank Verboven, and Stefano Verzillo. 2021. "Evaluating the impact of price caps-evidence from the European Roam-Like-at-Home regulation." *CEPR Discussion Paper No. DP16554*.

Cazaubiel, Arthur, Morgane Cure, Bjørn Olav Johansen, and Thibaud Vergé. 2022. "Paying for prominence and consumer prices: Evidence from Booking's Preferred Partner Program." *Mimeo*.

Chen, Jihui, and Qihong Liu. 2011. "The Effect Of Most-Favored Customer Clauses On Prices." *Journal of Industrial Economics*, 59(3): 343–371.

Chen, Nan, and Hsin-Tien Tiffany Tsai. 2023. "Steering via algorithmic recommendations." *RAND Journal of Economics*, forthcoming.

Decarolis, Francesco, Muxin Li, and Filippo Paternollo. 2023. "Competition and Defaults in Online Search." *CEPR Discussion Paper DP17779*.

de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review*, 110(9): 2964–96.

de Cornière, Alexandre, and Greg Taylor. 2019. "A model of biased intermediation." *RAND Journal of Economics*, 50(4): 854–882.

Direction Générale des Entreprises. 2022. "Hôtellerie : hôtels de tourisme et auberges collectives." *https://www.entreprises.gouv.fr/fr/tourisme/conseils-strategie/hotellerie-hotels-de-tourisme-et-auberges-collectives*, [Last accessed May 7, 2024].

Edelman, Benjamin, and Julian Wright. 2015. "Price coherence and excessive intermediation." *Quarterly Journal of Economics*, 130(3): 1283–1328.

Ennis, Sean, Marc Ivaldi, and Vicente Lagos. 2023. "Price-Parity Clauses for Hotel Room Booking: Empirical Evidence from Regulatory Change." *Journal of Law and Economics*, 66(2): 309–331.

Ershov, Daniel, and Matthew Mitchell. 2024. "The effects of influencer advertising disclosure regulations: Evidence from Instagram." *RAND Journal of Economics*, forthcoming.

European Commission. 2022. "Antitrust: Commission accepts commitments by Amazon barring it from using marketplace seller data, and ensuring equal access to Buy Box and Prime." *https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7777*, [Last accessed May 7, 2024].

European Commission. 2024. "Commission fines Apple over €1.8 billion over abusive App store rules for music streaming providers." *https://ec.europa.eu/commission/presscorner/detail/en/ip_24_1161*, [Last accessed May 7, 2024].

European Competition Network. 2017. "Report on the monitoring exercise carried out in the online hotel booking sector by EU competition authorities in 2016." *European Commission*.

Eurostat. 2024. "Net occupancy rate of bed-places and bedrooms in hotels and similar accommodation (NACE Rev. 2 activity I55.1) by NUTS 2 regions." *https://ec.europa.eu/eurostat/databrowser/view/TOUR_OCC_ANOR2/default/line?lang=en*, [Last accessed May 7, 2024].

Ezrachi, Ariel. 2015. "The competitive effects of parity clauses on online commerce." *European Competition Journal*, 11(2-3): 488–519.

Farronato, Chiara, Andrey Fradkin, and Alexander MacKay. 2023. "Self-Preferencing at Amazon: Evidence from Search Rankings." *AEA Papers and Proceedings*, 113: 239–43.

Feng, Josh, Thomas Hwang, and Luca Maini. 2023. "Profiting from Most-Favored-Customer Procurement Rules: Evidence from Medicaid." *American Economic Journal: Economic Policy*, 15(2): 166–197.

Gomes, Renato, and Andrea Mantovani. 2024. "Regulating Platform Fees Under Price Parity." *Journal of the European Economic Association*, fortchoming.

Gonzalo, Frédéric. 2016. "Hotels Promoting Direct Bookings: It's About Time!" *https://fredericgonzalo.com/en/hotels-promoting-direct-bookings-its-about-time/*, [Last accessed May 7, 2024].

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.

Gutierrez, German. 2022. "The Welfare Consequences of Regulating Amazon." *SSRN Working Paper 3965566*.

Hollenbeck, Brett. 2017. "The economic advantages of chain organization." *RAND Journal of Economics*, 48(4): 1103–1135.

HOTREC. 2015. "The European hospitality industry launches a campaign: 'Book Direct'." *https://2022.hotrec.eu/wp-content/customer-area/storage/2272073f40d84dc49b270273d10122e9/The-European-hospitality-industry-launches-a-campaign-Book-Direct-15-december-2015.pdf*, [Last accessed May 7, 2024].

HOTREC. 2020. "European Hotel Distribution Study 2020." *https://www.hotrec.eu/en/policies/european_hotel_distribution_study_2020_-_summary.html*, [Last accessed May 7, 2024].

Hunold, Matthias, Reinhold Kesler, and Ulrich Laitenberger. 2020. "Rankings of online travel agents, channel pricing, and consumer protection." *Marketing Science*, 39(1): 92–116.

Hunold, Matthias, Reinhold Kesler, Ulrich Laitenberger, and Frank Schlütter. 2018. "Evaluation of best price clauses in hotel booking." *International Journal of Industrial Organization*, 61: 542–571.

Hunold, Matthias, Ulrich Laitenberger, and Guillaume Thébaudin. 2022. "Bye-box: An analysis of non-promotion on the Amazon Marketplace." *CRED Working Paper 2022-4*.

Insee. 2016. "In Q4 2015, the number of tourism nights declined (-1.7% year-on-year)." *https://www.insee.fr/en/statistiques/2011367*, [Last accessed May 7, 2024].

Johansen, Bjørn Olav, and Thibaud Vergé. 2017. "Platform price parity clauses with direct sales." *University of Bergen*, Working Papers in Economics 01/17.

Johnson, Justin P. 2017. "The agency model and MFN clauses." *Review of Economic Studies*, 84(3): 1151–1185.

Kang, Zi Yang, and Shoshana Vasserman. 2022. "Robust bounds for welfare analysis." *NBER Working Paper 29656*.

Karle, Heiko, Martin Peitz, and Markus Reisinger. 2020. "Segmentation versus agglomeration: Competition between platforms with competitive sellers." *Journal of Political Economy*, 128(6): 2329–2374.

Kosová, Renáta, and Francine Lafontaine. 2012. "Much ado about chains: A research agenda." *International Journal of Industrial Organization*, 30(3): 303–308.

Mantovani, Andrea, Claudio A. Piga, and Carlo Reggiani. 2021. "Online platform price parity clauses: Evidence from the EU Booking.com case." *European Economic Review*, 131: 103625.

Marshall, James, Sophie Albrighton, and Grace Kim. 2021. "The UK CMA publishes its recommendation for replacing the retained Vertical Agreements Block Exemption Regulation." *https://www.covcompetition.com/2021/11/the-uk-cma-publishes-its-recommendation-for-replacing-the-retained-vertical-agreements-block-exemption-regulation/*, [Last accessed May 7, 2024].

Peitz, Martin. 2022. "The prohibition of price parity clauses and the Digital Markets Act." *Competition Policy International*.

Reimers, Imke, and Joel Waldfogel. 2023. "A Framework for Detection, Measurement, and Welfare Analysis of Platform Bias." *NBER Working Paper 31766*.

Roskis, Dan, and Thomas Strange. 2015. "France - Macron Law: A focus on online hotel reservation platforms." *https://www.eversheds-sutherland.com/global/en/what/articles/index.page?articleID=en/Competition_EU_and_Regulatory/Macron_Law_France*, [Last accessed May 7, 2024].

Scott Morton, Fiona. 2023. "Improving the contestability of e-commerce in two jurisdictions: the Amazon case." *Bruegel Policy Brief*, 22/23.

Singh, Nirvikar, and Xavier Vives. 1984. "Price and quantity competition in a differentiated duopoly." *Rand Journal of Economics*, 546–554.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199.

Teh, Tat-How, and Julian Wright. 2020. "Intermediation and steering: Competition in prices and commissions." *American Economic Journal: Microeconomics*, 14(2): 281–321.

Tirole, Jean, and Michele Bisceglia. 2023. "Fair gatekeeping in digital ecosystems." *TSE Working Paper 1452*.

Varian, Hal R. 1985. "Price discrimination and social welfare." *American Economic Review*, 75(4): 870–875.

Wang, Chengsi, and Julian Wright. 2020. "Search platforms: showrooming and price parity clauses." *RAND Journal of Economics*, 51(1): 32–58.

Wang, Chengsi, and Julian Wright. 2022. "Platform investment and price parity clauses." *Journal of Industrial Economics*, 71(2): 538–569.

Wang, Chengsi, and Julian Wright. 2023. "Regulating platform fees." *Mimeo*.

A The Economic Effects of Removing PPCs: Theoretical Hypotheses

Consider an economy with n hotels i $(i = 1, \ldots, n)$ that can sell their rooms on three channels j, $j = o, w, m$ with o standing for the OTA channel, w the WEB channel, and m for the INN channel, i.e., hotel direct booking via mail, calls or walk-ins. Note that, according to our definition above, the first two channels are observable, whereas the third one is not. There is no cost associated to selling through any of the channels, but o involves paying to OTAs a percentage fee, f_o, per transaction.

Define the demand function for a hotel and channel pair as $D_{ij}(p_{ij}, \mathbf{p_{-ij}})$, where p_{ij} is the price of the room in hotel i, bought through channel j and $\mathbf{p_{-ij}}$ is the vector of the prices of all other hotel-channel pairs. The demand function is downward sloping in p_{ij}, and non-decreasing in all other prices $\mathbf{p_{-ij}}$. The negative direct effect of a hotel-channel price on its demand is larger, in absolute value, than the positive indirect effects on other channels, i.e., $|{}^{\partial D_{ij}}/_{\partial p_{ij}}| > {}^{\partial D_{ij}}/_{\partial p_{-ij}}$.

To gain insights about hotel prices, we consider two regimes: first, if PPCs are imposed by OTAs and, second, if PPCs are not allowed. The profit function of hotel i, omitting the aguments in the demand functions for ease of notation, can be written as:

$$\pi_i(p_{ij}, \mathbf{p_{-ij}}) = p_{io}D_{io}(1 - f_o) + p_{iw}D_{iw} + p_{im}D_{im}. \tag{11}$$

The assumptions previously made hold, for example, in the demand system by Singh and Vives (1984), which has been extended and used in the context of platforms by Johansen and Vergé (2017); Calzada, Manna and Mantovani (2022); Karle, Peitz and Reisinger (2020), inter alios. To gauge more insights about the pricing behaviour of hotels, we specify such a demand system as follows:

$$D_{ij}(p_{ij}, \mathbf{p_{-ij}}) = \alpha - \beta_0(1 + \mathbb{1}_m\tau_m)p_{ij} + \beta_1 \sum_{k=1,\ldots,n}^{l=w,o,m} p_{kl}. \tag{12}$$

where D_{ij} is the demand faced by a hotel i on the channel j where the prices are given by the vector $(p_{ij}, \mathbf{p_{-ij}})$, α is a parameter representing the demand intercept, β_0 and β_1 are parameters capturing the price sensitiveness of the demand on a hotel's own channel or of a rival, $\mathbb{1}_m$ is an indicator function that switches on when the channel is m and τ_m captures the difference in price sensitiveness of hotel i's consumers opting for channel m, not visible to outsiders.

Under this demand specification, the FOCs as a function of the hotel's channel price, p, for a given vector of other prices $\mathbf{p_{-ij}}$, can be written as:

$$FOC_p(p, \mathbf{p_{-ij}}) = (3 - f_o)\left[\alpha + 3(n-1)\beta_1 p_{-ij} - 2\left(\beta_0 - (n-1)\beta_1\right)p\right], \tag{13}$$

with PPCs, and as:

$$FOC_w(p, \mathbf{p_{-ij}}) = \alpha + \beta_1[(4 - f_o) + 3(n-1)]p_{-ij} - 2\beta_0 p, \tag{14}$$

$$FOC_m(p, \mathbf{p_{-ij}}) = \alpha + \beta_1[(4 - f_o) + 3(n-1)]p_{-ij} - 2\beta_0(1 + \tau_m)p, \tag{15}$$

$$FOC_o(p, \mathbf{p_{-ij}}) = \alpha(1 - f_o) + \beta_1[(4 - f_o) + 3(n-1)(1 - f_o)]p_{-ij} - 2\beta_0(1 - f_o)p, \tag{16}$$

when PPCs are not imposed by OTAs.

We start by noting, from equation (13), that the second order conditions for a maximum of the profits require that the (negative) direct effects of a channel price on the demand are sufficiently larger compared to the indirect and positive effects, i.e., that $\beta_0 > (n-1)\beta_1$.

Focus then on the FOCs in (14)-(16). First, we can see that the FOC for channel m decreases faster than the one for channel w, as $-2\beta_0(1+\tau_m) < -2\beta_0$. As the intercept of both FOCs with the vertical axis is identical, we can conclude that the FOC for channel m is always lying below the one for channel w in the first quadrant and, hence, crosses the horizontal axis for a lower price. In other words, $p_m^* < p_w^*$.

Second, the FOC of channel o has a lower intercept with the vertical axis than that of channel w and m. This can be seen by comparing the first two terms on the right hand side of (16) and of (14) (or (15)), respectively. At the same time, the FOC of channel o also decreases at a lower rate than the other two, as $-2\beta_0(1-f_o) > -2\beta_0$. As the FOCs are linear in p, they cross at most once in the first quadrant. The crossing takes place for a lower p: (i) the higher is the direct price effect β_0, and (ii) the lower are the parameters affecting the intercept (α, β_1), but it is not affected by f_o. If that is the case, then the FOCs of channel w and, *a fortiori*, channel m, cross the horizontal axis for a lower value of p. In other words, $p_m^* < p_w^* < p_o^*$.

Finally, the FOC when PPCs are imposed, (13), is scaled up by a factor $(3 - f_o)$, implying it has a much higher vertical intercept, but it is also steeper than the other FOC functions. It is not possible to know *a priori* if the FOC under PPCs crosses the horizontal axis for a higher or lower value of p than the other FOC functions. However, it is possible that the price with PPCs, p^*, is higher than all the prices when these clauses are not present, even if there are *no changes* to the OTA fee due to the impossibility of adopting PPCs.

Figure 1 in the main text provides an illustration of such a case, based on an example with two hotels. The figure plots all the FOCs, (13)-(16), as a function of the price p. The equilibrium prices entail that the FOCs are zero, i.e., they can be read in the figure where the functions cross the horizontal axis. The above insights have implications for the resulting equilibrium prices, and generate the Theoretical Predictions 1 and 2 in the main text.

B Summary of Distribution Channels

Our sample includes observations from several distribution channels, covering both online and offline reservations. For online channels, our dataset distinguishes between Online Travel Agencies (OTA) and Website Direct (WEB). The OTA channel include transactions made on platforms such as Booking.com, Expedia, as well as Ctrip and Hotel.de, among others. The WEB channel includes bookings made on the official websites of hotels. The offline channels are Hotel Direct (INN), Central Reservation Office (CRO), Global Distribution System (GDS), Wholesale (WHOLESALE), and a residual category for all other offline bookings (OTHER).

In particular, individual hotels and hotel chains control the INN and CRO channels. The INN channel is the main offline direct sales channel for hotels. It comprises of direct phone calls, e-mail reservations, walk-ins. The CRO channel includes bookings made by calling the chain-specific call centers. GDS is a platform system where hotels may sell their rooms, and travel agencies may book rooms for their clients. It is one of the predecessors of OTAs. Sabre and Amadeus are two major systems included in the GDS channel. The WHOLESALE channel is unique in that capacities are often offered to travel agencies before the season begins. These rooms may be included in package holidays or sold to other sellers.

In our analyses, we focus on three distribution channels—OTA, WEB, and INN. The first two are directly affected by the prohibition of PPCs, and the last one is a channel directly controlled by individual hotels. Table B.1 reports the shares of different reservation channels by year. In the time span that we consider, we note that the share of the online channels increased, whereas the share of other offline channels decreased, with the exception of GDS. Table B.2 summarises the different booking channels available to the hotels in our sample, including their ownership and their cost of usage.

Table B.1—Shares of Room Nights Booked Across Channels By Year

Channel	2014	2015	2016	2017	Average
<u>Online</u>					
[6] OTA (Online Travel Agency)	15.8	17.4	18.5	19.6	17.7
[2] WEB (Official Website)	15.7	16.3	18.0	18.5	17.0
<u>Offline</u>					
[2] INN (Offline Direct)	48.6	46.7	44.5	43.2	45.9
[6] GDS (Global Distribution System)	12.0	12.5	12.5	13.4	12.5
[3] CRO (Central Reservation Office)	4.4	4.2	3.9	3.4	4.0
[4] WHOLESALE (Wholesale)	2.7	2.1	1.8	1.1	2.0
[4] OTHER (Other Offline Bookings)	0.9	0.9	0.9	0.8	0.9
Total (%)	100	100	100	100	100

Note: [6]Platform, [2]Hotel-owned, [3]Chain-owned, [4]Other.

Table B.2—Sales Channel Information For Hotels

Channel	Ownership	Commission Costs
Online		
OTA (Online Travel Agency)	Platform	High
WEB (Official Website)	Hotel-Owned	Low
Offline		
INN (Offline Direct)	Hotel-Owned	Low
GDS (Global Distribution System)	Platform	High
CRO (Central Reservation Office)	Chain-Owned	Low
WHOLESALE (Wholesale)	Other	N/A
OTHER (Other Offline Bookings)	Other	N/A

Note: This table summarises the different booking channels available to chain hotels. The "Commission Costs" column broadly indicates whether the costs of finalizing a booking through each channel are high or low for the individual hotels. Information regarding the WHOLESALE and OTHER channels is limited. Hence, their commission rates are denoted as N/A. Commission costs usually come in the form of commission rates to third-party platforms or agents, but sometimes, individual hotels also pay small rates to the hotel chains. Bookings finalized through channels owned by individual hotels or hotel chains are almost costless versus bookings made through third-party channels.

C DID Event Study Plots

C.1 DID Imputation

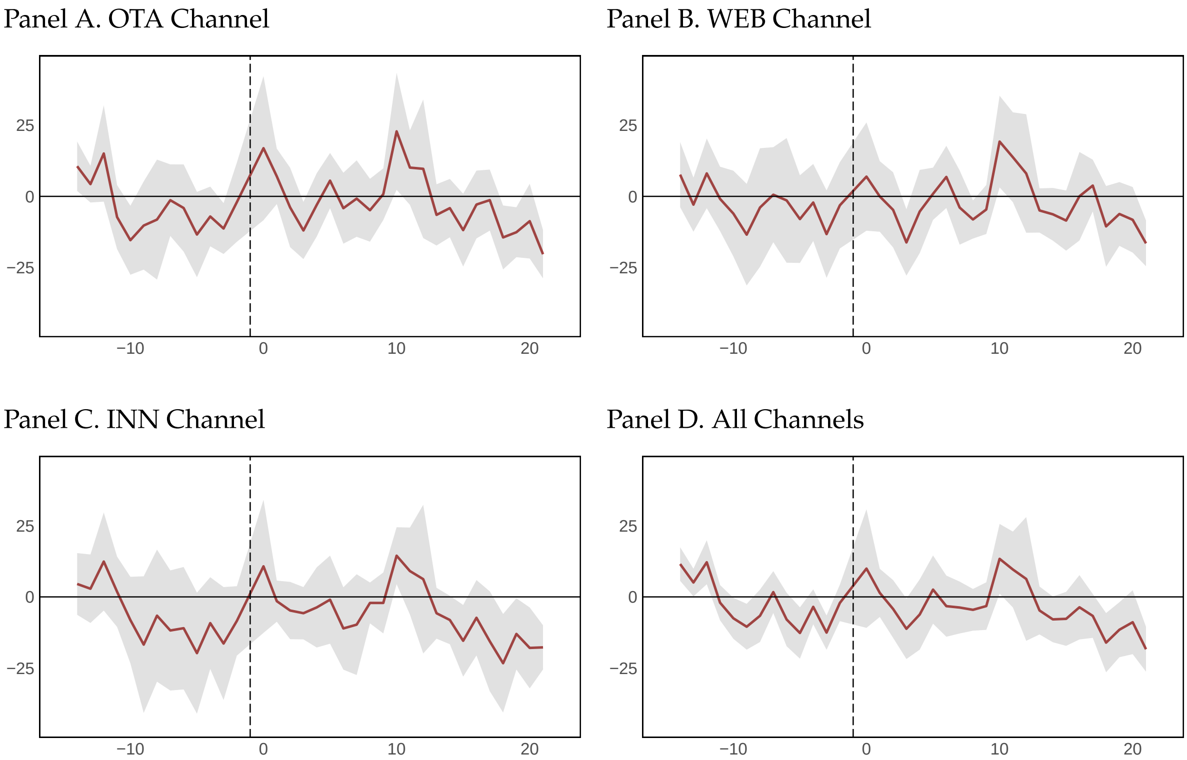


Figure C.1: Event Study for Log Prices — France vs Control

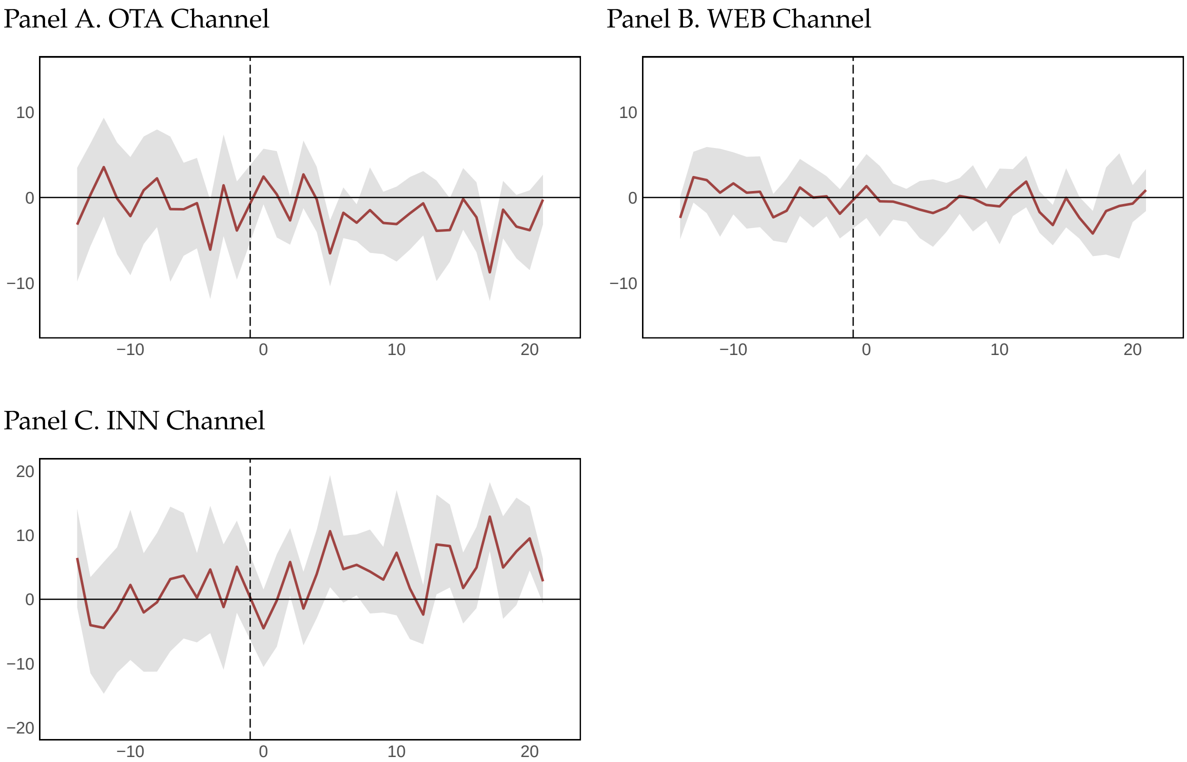


Figure C.2: Event Study for Channel Shares — France vs Control

D Anticipation and Lagged Effects

Anticipation of the Macron Law should have negligible effects on French hotel prices. On the one hand, it would be unlikely for the platforms to end their PPCs with hotels in advance of the legally imposed dates. On the other hand, hotels would be unable to lower the prices on their official websites beforehand, as it would be a breach of the PPCs. Our findings confirm these conjectures. As shown in Panel A of Table D.1, the price effects of shifting the treatment timing by one month before the Macron Law are relatively smaller, indicating that the legislation was not anticipated in practice.

We also consider the possibility that the treatment effects might be *lagged*. Mantovani, Piga and Reggiani (2021) observe that there may exist a large gap between the booking date and the check-in date of hotel rooms. In other words, the rooms booked after the Macron Law may undergo weeks before they are checked in. Prices may also take time to adjust as hotels modify their pricing strategies to adapt to the new legislation. To account for such a lagged effect, we shifted the treatment timing by one month after the Macron Law. As shown in Panel B of Table D.1, we find qualitatively similar but more pronounced effects as our main results, suggesting that the effects of the legislation may have been lagged.

Table D.1—Estimated Effects of the Macron Law: Anticipation and Lags

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. Anticipation Effects				
$\tau^{\text{MC-NN}}$	−0.936	−1.405	−4.504	−2.808
	(2.574)	(2.167)	(2.130)	(2.052)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,406	5,418	5,302	29.175
Panel B. Lagged Effects				
$\tau^{\text{MC-NN}}$	−3.224	−2.651	−6.633	−4.366
	(2.853)	(2.941)	(3.003)	(2.398)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,406	5,418	5,302	29.175

Note: This table reports the estimated anticipation and lagged effects of the Macron Law on prices. The analyses are performed using the MC-NN estimator following Equation (7). The WEB, OTA, INN column headers indicate the coefficients estimated using subsets of data from the respective channels. The last column reports the estimated coefficients using data from all sales channels. Panel A reports the anticipation effects, and Panel B reports the lagged effects. Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times.

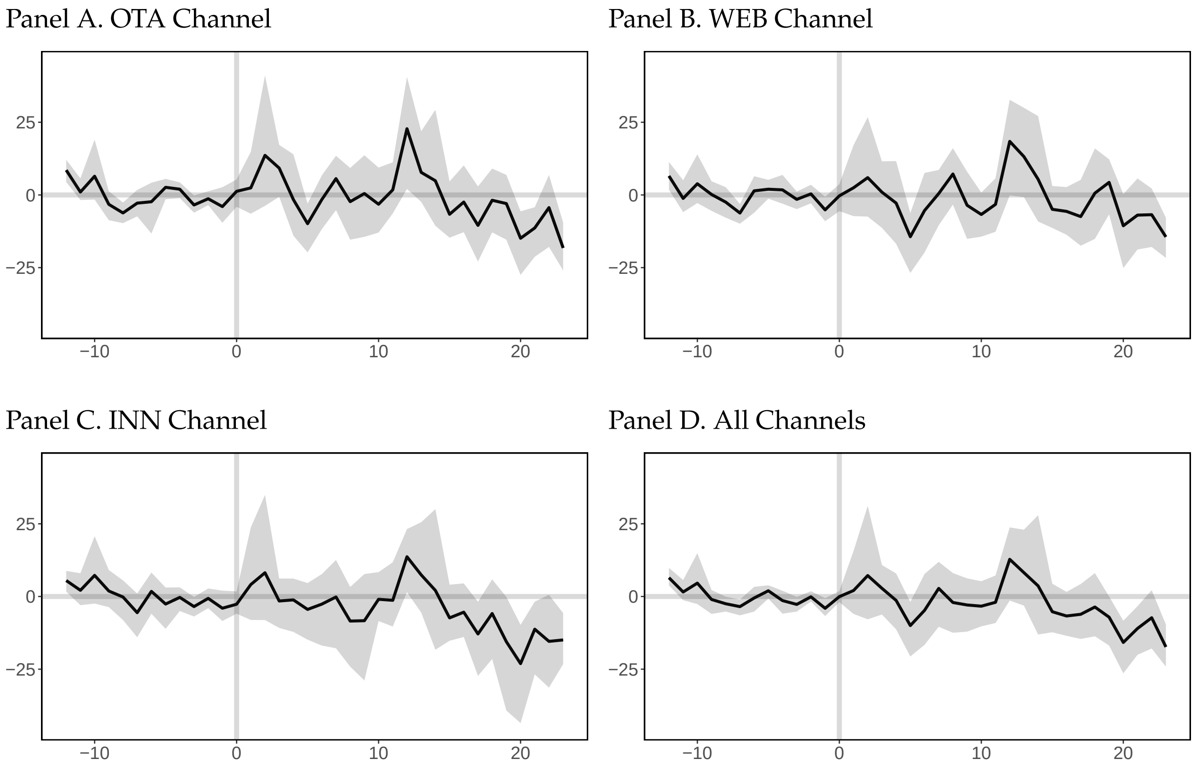


Figure D.1: MC-NN — Anticipation Effects of the Macron Law on Prices

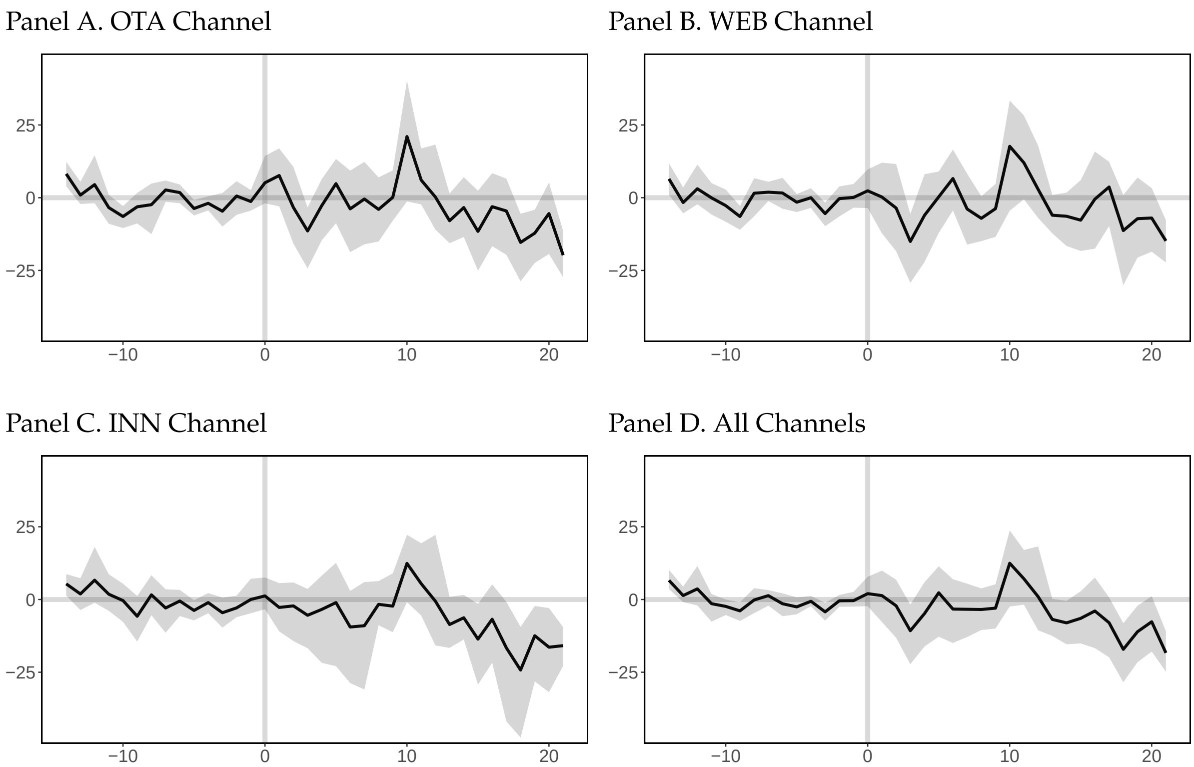


Figure D.2: MC-NN — Lagged Effects of the Macron Law on Prices

E The November 2015 Paris Terrorist Attack

The 2015 Paris Terrorist Attack was the most severe terrorist attack (130 deaths, 416 injuries) that occurred in Europe in the 2010s. The tragedy happened on 15th November 2015 in Paris, one of the world-renowned European cities known for its fashion, culinary arts, and culture. Table E.1 reports the combined price effect of the Macron Law and the November 2015 Paris Terrorist Attack. The larger magnitude of the coefficients is consistent with the possibility that the terrorist attacks had a further negative effect on the prices of the treated hotels.

Table E.1—Price Effects of Prohibiting PPCs and the Paris Terrorist Attack

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. Hotel Group 1				
$\tau^{\text{MC-NN}}$	−3.922	−3.484	−5.111	−4.369
	(2.840)	(2.158)	(1.706)	(1.916)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,730	5,742	5,626	30,959
No. of Hotels	166	166	165	166

Note: This table reports the combined price effects of the Macron Law and the November 2015 Paris Terrorist Attack. The analyses are performed using the MC-NN estimator. The WEB, OTA, INN column headers indicate the coefficients estimated using subsets of data from the respective channels. The last column reports the estimated coefficients using data from all sales channels. Panel A reports the MC-NN estimates using Equation (7). Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times.

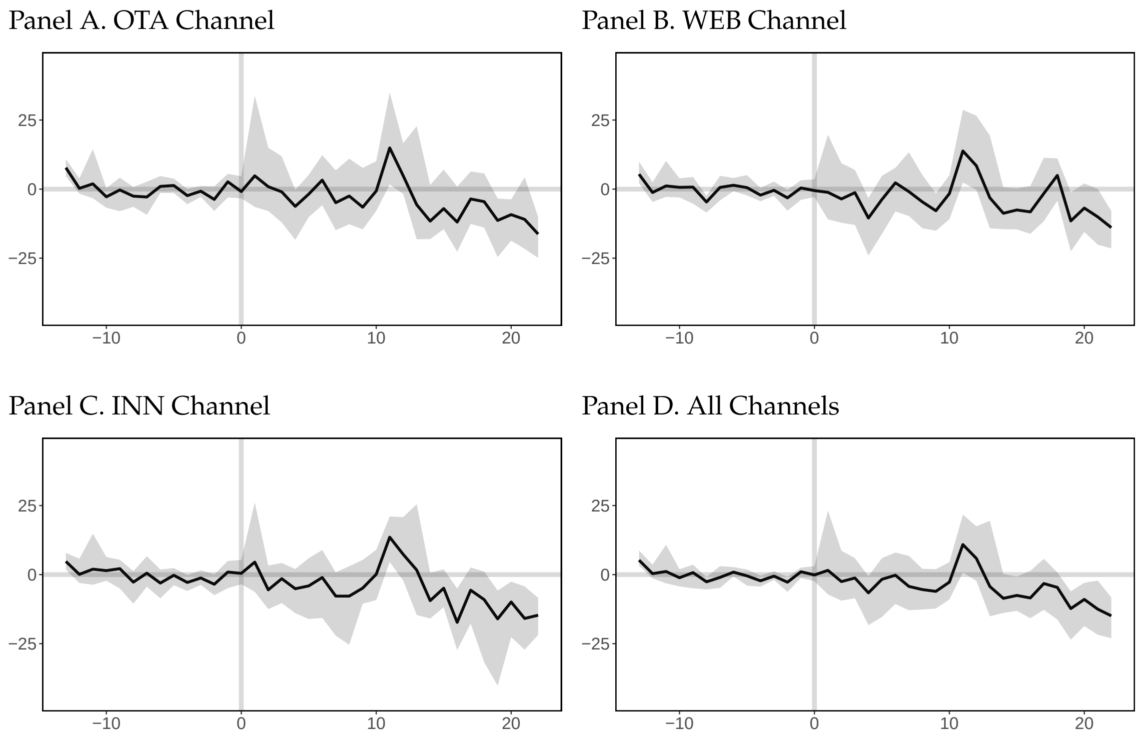
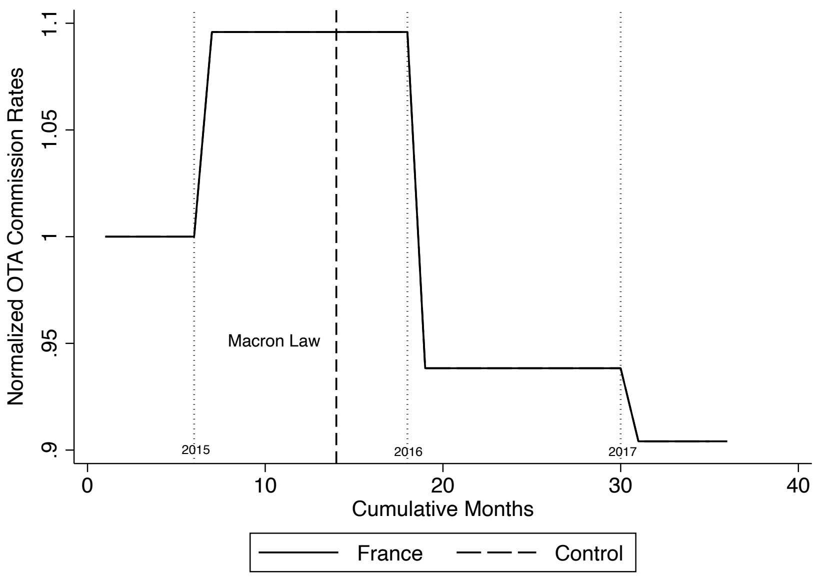


Figure E.1: MC-NN — Anticipation Effects of the Macron Law on Prices

F OTA Commission Rates: Hotel Group 2

The descriptive exhibit in this appendix are generated using data from 5 hotel brands of Group 2. Figure 4 in the main text is based on data from 10 hotel brands of Group 1, whereas information regarding the OTA commission rates were not provided by Group 3. Due to confidentiality concerns, we only show the normalized OTA commission rates for the two hotel groups, with the rates at Cumulative Month 1 set to 100%.

Figure F.1: Normalised OTA Commission Rates: Group 2



Although the data is partial and quite aggregated, these descriptive exhibits reveal a number of insights. First, substantial changes in OTA commission rates appear to occur near the end of each fiscal year (dotted lines). This suggests that the groups may have been renegotiating their commission rates with the OTAs since the Macron Law (dashed line) was implemented. Indeed, for both groups (Figure F.1 for Group 2 and Figure 4 for Group 1 in the main text), the rates went down in the years following the policy intervention, although not instantly after the enactment of the Macron Law.

Second, Figure F.1 reports the same average rates for hotels in France and in countries of the control group. Unfortunately, we were not able to confirm whether this is because the hotels are charged the same fee throughout the countries in our sample or because Group 2 only provided aggregate data. This is unlike Figure 4 in the text, which indicates that since 2016 the commission rates paid by hotels of Group 1 were lower in France than in the countries of the control group.

G Price Effects For Hotel Group 1

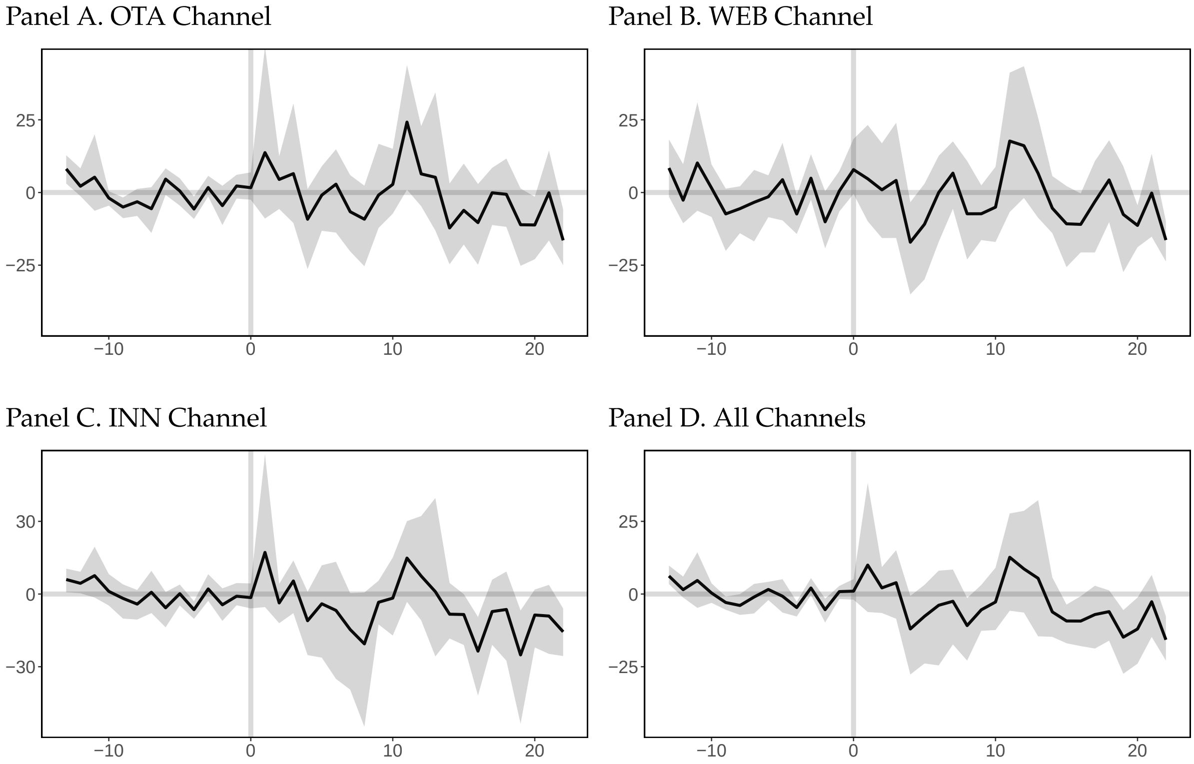


Figure G.1: MC-NN — Price Effects For Hotel Group 1

H Heterogeneous Effects: Pre-Treatment OTA Reliance

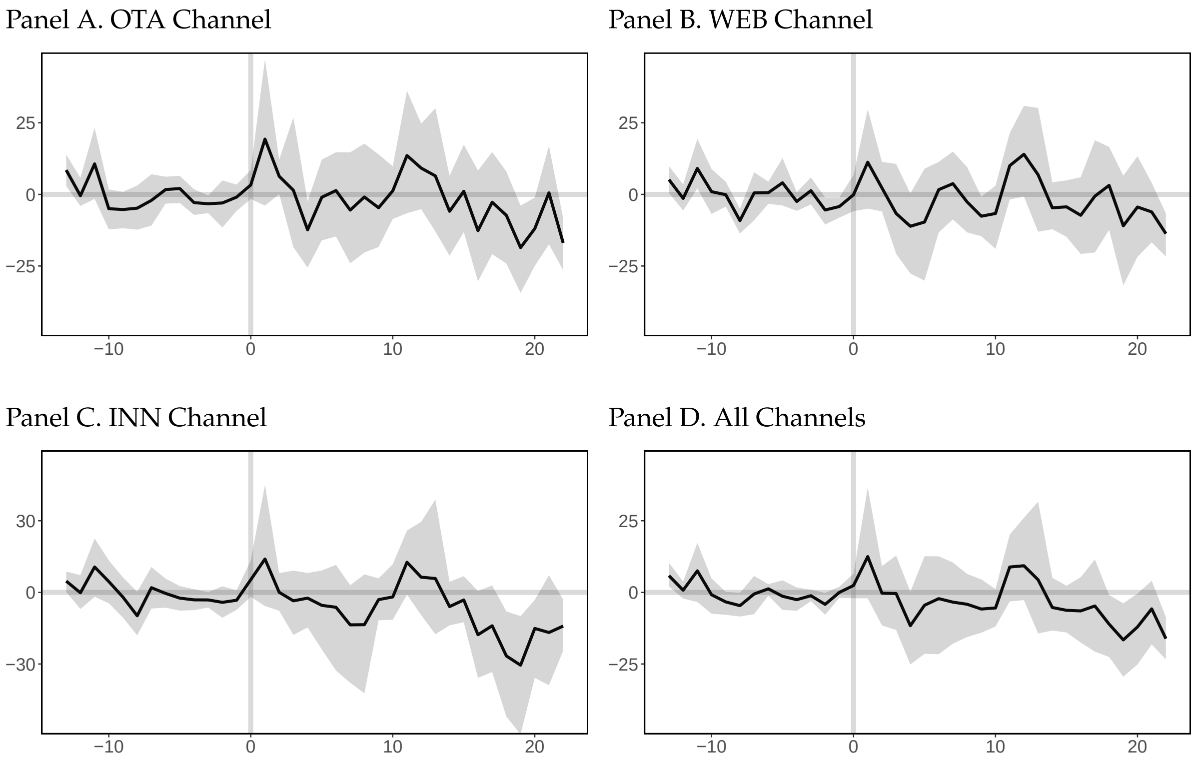


Figure H.1: MC-NN Analysis of Prices — OTA Reliance Less Than 20%

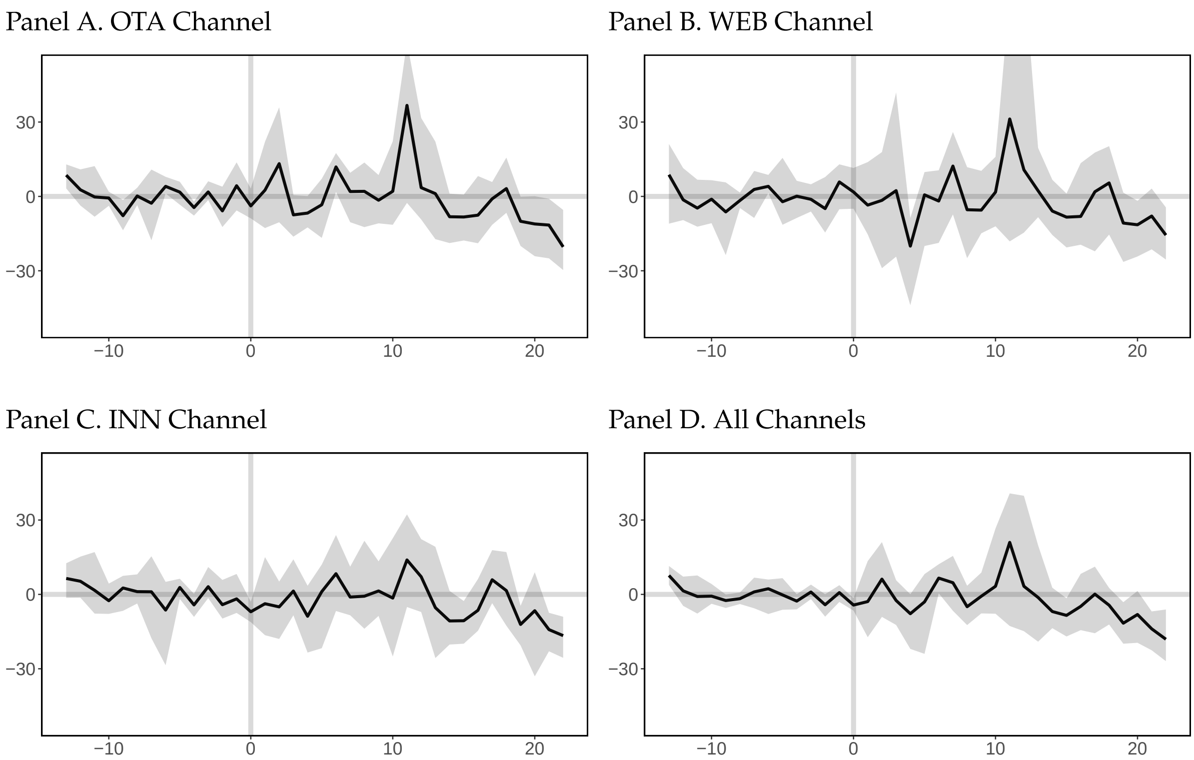


Figure H.2: MC-NN Analysis of Prices — OTA Reliance More Than 20%

I Heterogeneous Effects: Pre-Treatment Occupancy Rate

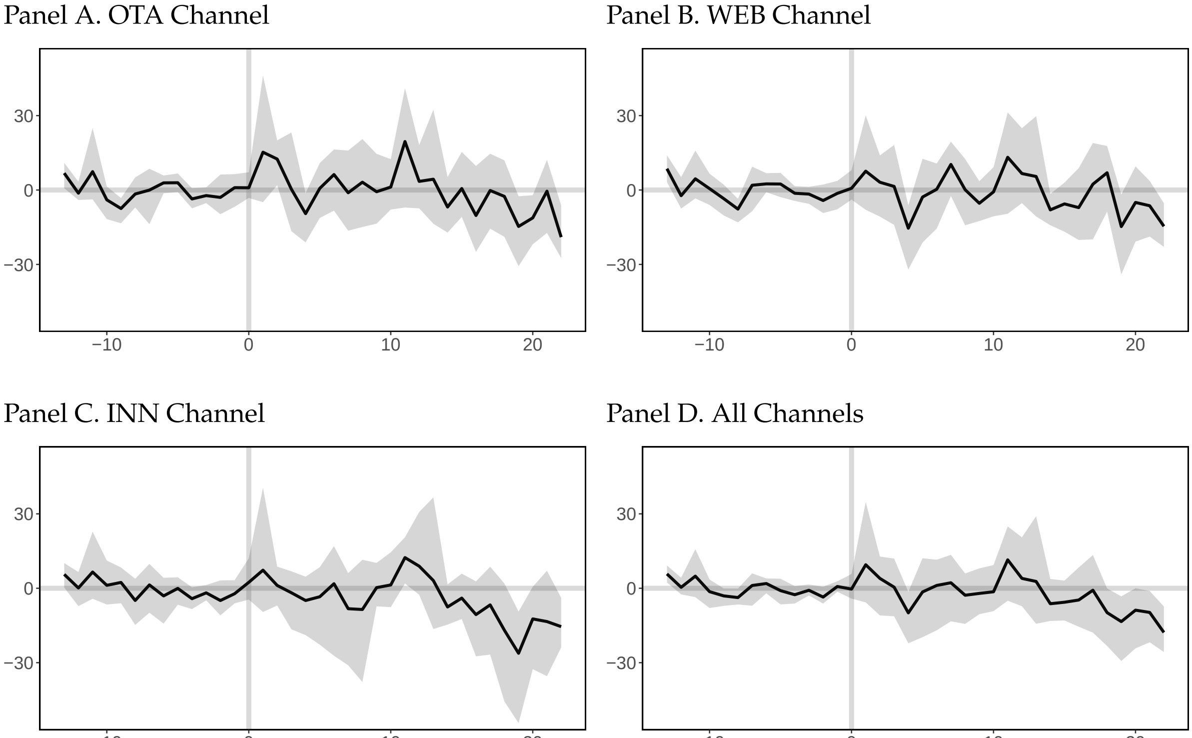


Figure I.1: MC-NN Analysis of Prices — Occupancy Rate Less Than 65%

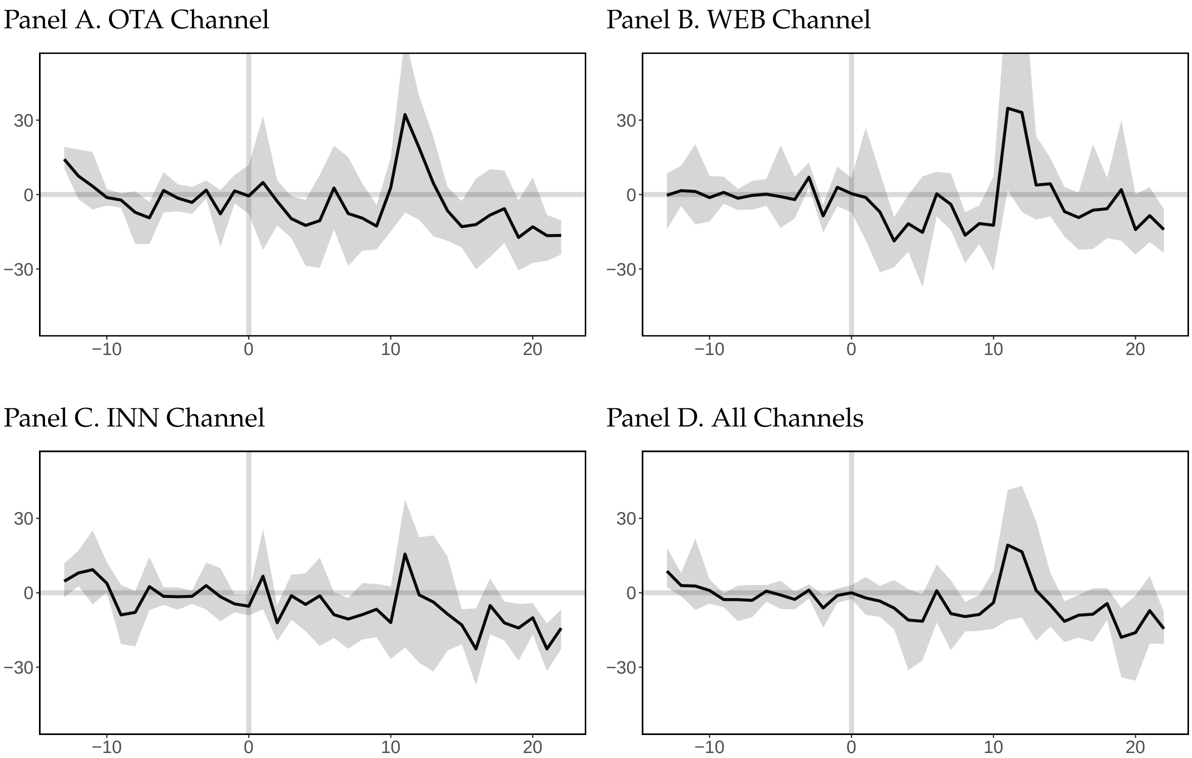


Figure I.2: MC-NN Analysis of Prices — Occupancy Rate More Than 65%

J Additional Information on Welfare Analysis

J.1 Estimation using Kang and Vasserman (2022)

Table J.1 presents the number of 3-star to 5-star hotels in France in 2017 (Direction Générale des Entreprises, 2022). We note that the number of establishments does not vary drastically yearly. Hence, these numbers are acceptable approximations for the number of 3-star to 5-star hotels since the Macron Law in August 2015. There are approximately 6,000 3-star hotels in France and around 2,000 4-star and 5-star hotels.

Table J.1—Number of 3-Star to 5-Star French Hotels in 2017

Region	3 Stars		4 Stars		5 Stars	
	Number	Capacity	Number	Capacity	Number	Capacity
Auvergne-Rhône-Alpes	879	32,686	247	14,490	60	2,707
Bourgogne-Franche-Comté	305	10,237	60	2,530	5	234
Bretagne	330	11,104	76	3,905	9	722
Centre-Val de Loire	218	7,826	55	2,703	3	136
Corse	170	6,223	50	1,595	11	443
Grand Est	461	17,487	104	6,189	13	552
Hauts-de-France	253	11,268	49	3,980	7	491
Île-de-France	1,011	55,601	485	48,624	74	7,480
Normandie	266	10,103	54	3,373	10	888
Nouvelle-Aquitaine	558	19,212	142	7,390	25	1,143
Occitanie	620	25,228	140	9,141	13	591
Pays de la Loire	246	9,784	57	3,486	5	377
Provence-Alpes-Côte d'Azur	656	24,105	242	15,970	86	5,639
Total	5,973	240,864	1,761	123,376	321	21,403

Note: This table reports the number of 3-star to 5-star hotels in France in 2017. The number of hotels is also divided by the main regions in France. Capacity refers to the total number of rooms in a given region.

To obtain the overall Δ CS for the population of French hotels in in Table 7, we first calculate the bounds of Δ CS for an average, representative hotel of our sample, and apply the appropriate scaling factor. The scaling factor is a ratio between the average occupancy rate of hotels in our sample and the overall population, to account for the fact that our hotels have on average an higher occupancy rate than the rest. We then multiply the scaled Δ CS of the representative hotels of each star rating by the number of hotels in Table J.1 to obtain the values in Table 7.

Table J.2—Relative Gains in Consumer Surplus (Sample)

	Varian Lower Bound (1)	CES Lower Bound (2)	Linear Upper Bound (3)	Varian Upper Bound (4)
3-Star	29,483	33,405	33,443	37,398
4-Star	178,074	193,562	194,103	210,144
5-Star	496,032	532,186	533,733	571,437
Overall	703,589	759,153	761,279	818,979

Note: This table reports the estimated relative gains in consumer surplus of the Macron Law by comparing the changes in consumer surplus between France and the control countries for the 22 months after the legislation covered by our sample. The gains are calculated for the direct offline channel, which underwent statistically significant price reductions following the Macron Law. The bounds are calculated following the procedures proposed by Kang and Vasserman (2022) and calculated using equations (8) to (10). The units are in euros.

Table J.2 presents the robust bounds for the relative changes in consumer surplus induced by the Macron Law for the French hotels in our sample. We focused on the direct offline channel, INN, as its prices underwent significant reductions. For each star rating, we follow the same procedure described above and multiply the representative Δ CS by the number of hotels of each star rating in our sample. The welfare bounds are calculated using equations (8) to (10) following the procedures proposed by Kang and Vasserman (2022), and the units are in euros.

J.2 Estimation using the ATT

To calculate the welfare implications of the Macron Law using the ATT estimated in our study, we first obtained monthly room nights sales for French hotels by star ratings through INSEE, presented in Table 8, Column (1). Only data for the combined room nights of 4 and 5-star hotels is available.

The overall Δ CS is calculated using the estimated coefficients for the ATT obtained using the MC-NN estimator, then multiplied by the total room nights, and then, the share of the direct offline channel, INN. To account for the price differences between our sample and the population, we scale the welfare effects by the ratio of occupancy rates and account for the potential differences in INN shares and magnitudes of the ATT.

Table J.3—Approximated ΔCS using ATT (France)

	ATT (1)	Room Nights (2)	INN Share (3)	Mean Price (4)
3 Stars	−3.251	92.3	37.8%	€ 104.2
4 & 5 Stars	−6.309	59.1	55.1%	€ 184.4

Note: This table reports the components used in the calculation of welfare bounds in Table 8. Column (1) reports the price effects of the Macron Law on INN prices, estimated using Equation (7). The robust standard errors are clustered at the city level, and the non-parametric bootstrap is performed 1,000 times. Column (2) reports the number of room nights of French hotels by star ratings. The units are in millions. Column (3) reports the post-legislation INN share of hotels in our sample. This is most likely an upper bound of INN shares for French hotels, and the Lower Bound is calculated by assuming 30% for 3-star hotels and 40% for 4 & 5-star hotels. Column (4) reports the average post-legislation price for INN channels of our sample. Accordingly, we also scale down the bounds in Table 8 by a price ratio.

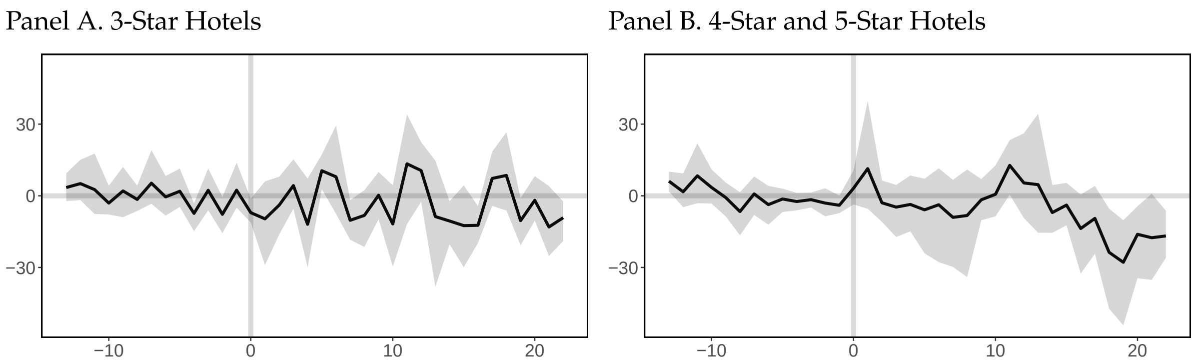


Figure J.1: MC-NN Analysis of INN Prices — Hotels by Star Ratings

K Anecdotal Evidence of PPCs and Their Monitoring

This Appendix provides anecdotal evidence on PPCs and rate monitoring by OTAs. Figure K.1 is a communication from Booking.com to a client in Italy. The communication informs the client that their contract will change and PPCs will be removed from it from the 29th of August 2017, the date in which the Italian law entered into force.

In the last part (full translation available upon request), Booking.com states: “In order to direct the largest number of customers from all over the world to your facility, we encourage you to provide Booking.com with correct and equal access to all the rooms, conditions and rates available during our collaboration (including the high and low season periods, and the periods of trade fairs, congresses and special events). We also guarantee that we will continue to do our best to provide you with better services and conditions compared to our competitors, in the hope that you choose to reward us by providing us with the best rates, conditions and availability.”

Booking.com

Gentile Partner,

In base alla nuova Legge n. 124/17 del 4 agosto, la preghiamo di considerare questa lettera come una notifica e conferma ufficiale di come intendiamo continuare a condurre la nostra collaborazione alla luce della nuova normativa.

La preghiamo di prendere atto di un'ulteriore modifica al nostro contratto (comprensivo di modifiche e da ora in poi denominato il **“Contratto”**) con lei (la **“Struttura”**), riguardo a Parità di Tariffe e Condizioni (come definita nel Contratto).

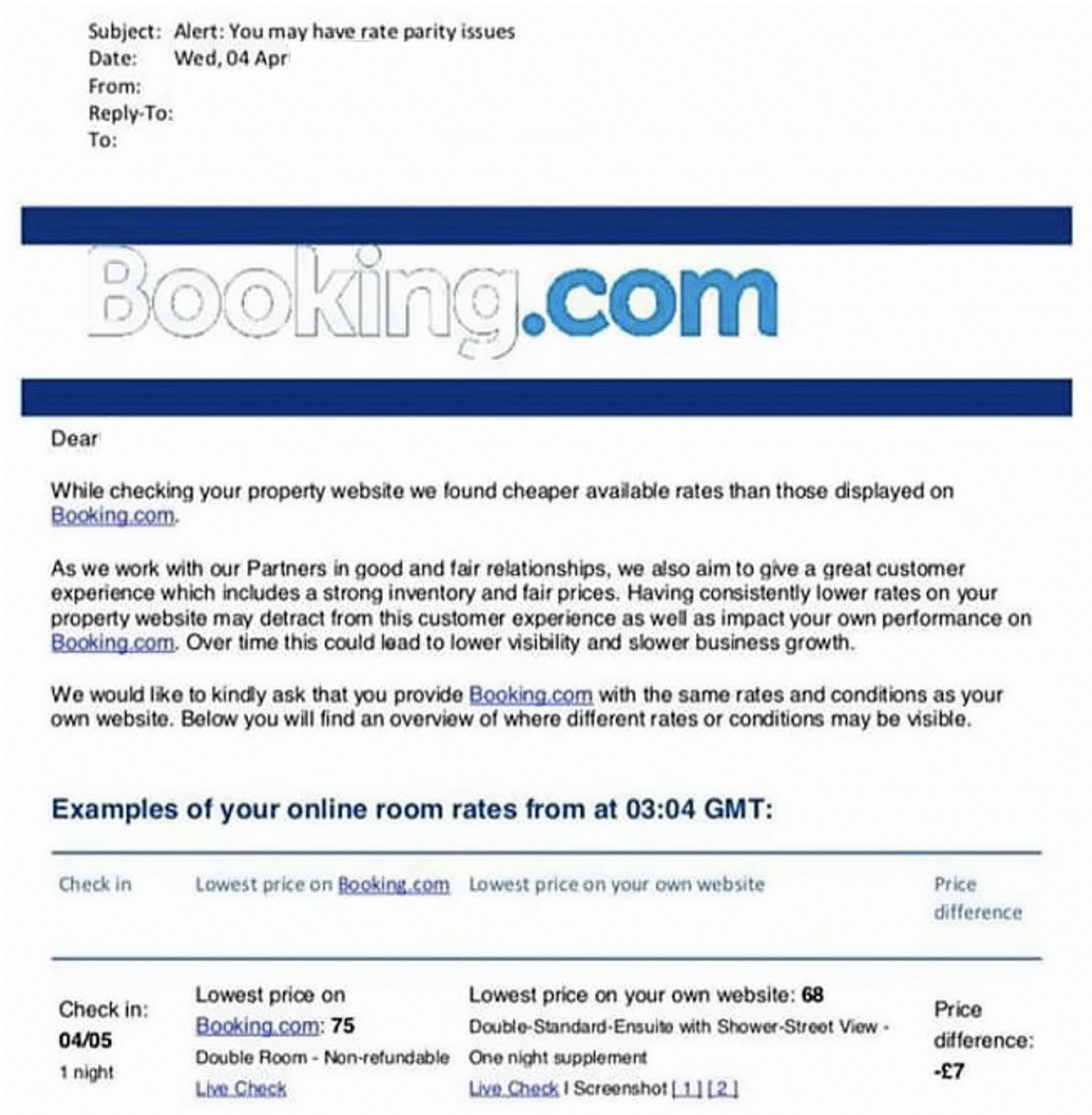
A partire dalla data di entrata in vigore della Legge (ovvero il 29 agosto 2017, qui denominata **“Data effettiva”**), Booking.com elimina e rimuove la Parità di Tariffe e Condizioni presenti nel Contratto. Tutti gli obblighi e le garanzie relativi a questo aspetto (inclusi diritti di sospensione/terminazione e obblighi di indennizzo) sono pertanto eliminati e annullati.

Per indirizzare il maggior numero di clienti da tutto il mondo verso la sua struttura, la incoraggiamo a fornire a Booking.com un corretto ed equo accesso a tutte le camere, condizioni e tariffe disponibili durante la nostra collaborazione (inclusi i periodi di alta e bassa stagione e i periodi relativi a fiere, congressi ed eventi speciali). Inoltre, le garantiamo che continueremo a fare del nostro meglio per fornirle servizi e termini migliori rispetto ai nostri concorrenti, nella speranza che in cambio lei scelga di premiarci fornendoci le migliori tariffe, condizioni e disponibilità.

Se dovesse avere dubbi o domande su questa lettera, la invitiamo a contattare Booking.com tramite il suo referente, che sarà felice di assisterla.

La ringraziamo per il suo continuo supporto e per la sua collaborazione.

Figure K.1: The Prohibition of PPCs in Italy and Booking.com’s Communication to a Client



Subject: Alert: You may have rate parity issues
Date: Wed, 04 Apr
From:
Reply-To:
To:

Booking.com

Dear

While checking your property website we found cheaper available rates than those displayed on Booking.com.

As we work with our Partners in good and fair relationships, we also aim to give a great customer experience which includes a strong inventory and fair prices. Having consistently lower rates on your property website may detract from this customer experience as well as impact your own performance on Booking.com. Over time this could lead to lower visibility and slower business growth.

We would like to kindly ask that you provide Booking.com with the same rates and conditions as your own website. Below you will find an overview of where different rates or conditions may be visible.

Examples of your online room rates from at 03:04 GMT:

Check in	Lowest price on Booking.com	Lowest price on your own website	Price difference
Check in: **04/05** 1 night	Lowest price on Booking.com: **75** Double Room - Non-refundable Live Check	Lowest price on your own website: **68** Double-Standard-Ensuite with Shower-Street View - One night supplement Live Check I Screenshot [1] [2]	Price difference: **-£7**

Figure K.2: The Monitoring of PPCs: Evidence from the UK. Source: Mail Online.

Moreover, there is evidence that OTAs have been monitoring client hotels' pricing behavior before and after the removal of PPCs. For example, Figure K.2 reports the communication betweenBooking.com and a client hotel in the UK, where Narrow PPCs are still legally enforced. In the email, Booking.com informs the client that they have detected a cheaper room rate on the hotel's website.

Figure K.3 provides a similar example from a Facebook forum for Italian hoteliers. At the time of the post (November 2017), all types of PPCs were already prohibited in Italy. In the post, a forum member states that: "Once again Expedia unduly penalizes me for a non-existent parity violation detected by their ratechecker". In the message, Expedia suggests to the user, "Take care of all the things that negatively affect your score, making sure that rates and availability on Expedia are always competitive."

The user and fellow forum members who replied to the post note how Expedia's check has not focused on the same type of room: a junior suite on Expedia with the price of EUR 122.39 is compared with a Twin/Double Room sold on Booking.com for EUR 95.00.

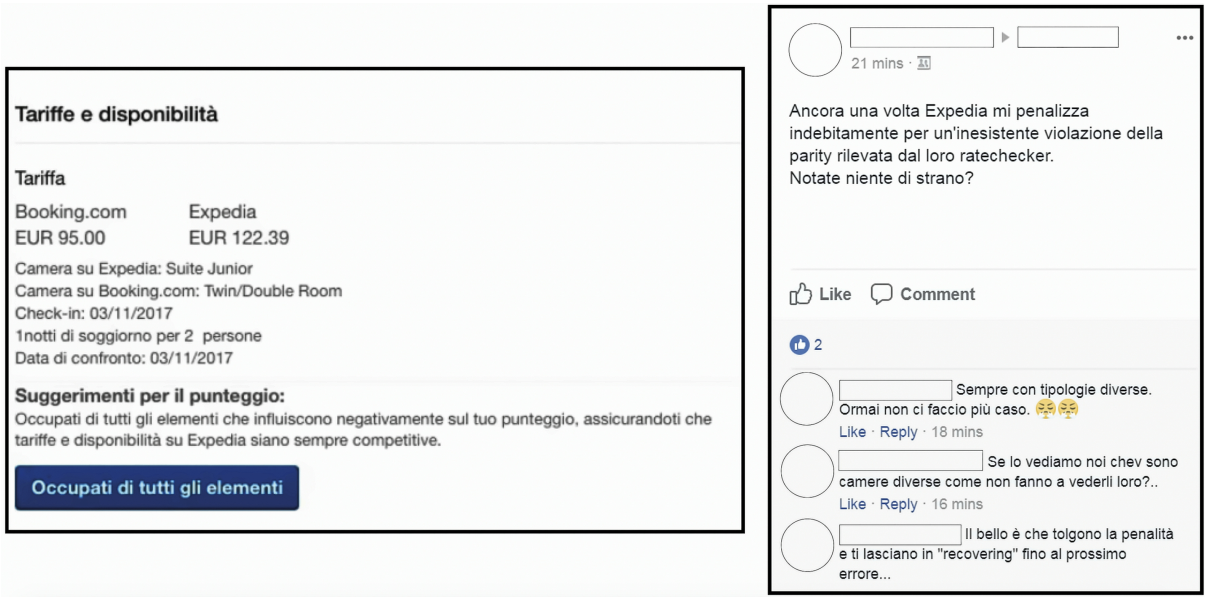


Figure K.3: The Monitoring of PPCs: Evidence from a Facebook Forum of Italian Hoteliers