The Price Effects of Prohibiting Price Parity Clauses: Evidence from Global Hotel Chains*

Jack (Peiyao) Ma † Andrea Mantovani ‡ Carlo Reggiani §

Annette Broocks ¶ Néstor Duch-Brown ‖

January 2026

Abstract

Dominant platforms like Booking.com have often imposed Price Parity Clauses to prevent 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 global hotel groups. Our analysis reveals limited and non-significant price effects for rooms sold through consumer-visible channels, such as hotels' websites or online travel agencies. However, we document a significant price reduction on sales channels not visible to consumers, such as direct offline bookings. Additionally, we identify a significant shift in the share of bookings from online travel agencies to the hotels' direct offline channels.

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

*The views and opinions expressed in this paper are the authors' and do not necessarily reflect those of the European Commission. We are deeply grateful to the Editor and three anonymous referees for their insightful comments and constructive suggestions. We especially thank Laura Lasio for very detailed comments. We also thank Mark Anderson, Marc Bourreau, Giulia Canzian, Grazia Cecere, Stefano Comino, Scott Cunningham, Francesco Decarolis, Chiara Farronato, Roxana Fernández, Amy Finkelstein, Jasmin Fliegner, Bernhard Ganglmair, Bjørn-Olav Johansen, Muxin Li, Helena Perrone, Claudio Piga, Stephen Ross, Pedro Sant'Anna, Stefano Verzillo, Mazhar Waseem, and seminar participants in CEMFI, Genova, JRC Seville, Oxford, UEA Norwich, the EARIE Conference (Rome, 2023), the EEA-ESEM Congress (Barcelona, 2023), ZEW ICT Conference (Mannheim, 2024), the Platform Strategy Research Symposium (Boston, 2024), the Jornadas de Economía Industrial (Sevilla, 2024), the Hospitality Innovation Series (IHPI) event "DMA: What can we expect after 6 months?" (Barcelona, 2024), the Senior Distribution Executive Roundtable "The Impact of the DMA in the Hospitality Industry" (London, 2025) for helpful remarks and discussion. We also thank Lucy Scioscia for her editorial assistance. The usual disclaimer applies.

†Corresponding author. University of Oxford, Oxford, UK. Email: peiyao.ma@oxfordmartin.ox.ac.uk.

‡TBS Business School, Toulouse, France. Email: a.mantovani@tbs-education.fr.

§European Commission JRC, Seville, Spain and Department of Economics, University of Manchester, Manchester, UK. Email: Carlo.REGGIANI@ec.europa.eu.

¶BEREC Office, Riga, Latvia. Email: Annette.BROOCKS@berec.europa.eu.

‖European Commission, Joint Research Centre, Seville, Spain. Email: Nestor.DUCH-BROWN@ec.europa.eu.

1 Introduction

In today's highly digitised 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 offered by the platforms. For every intermediated transaction, the platforms receive a commission fee, which is usually proportional to the transaction 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 maximise the number of transactions that consumers finalise through them, and for this purpose, they may adopt specific contractual arrangements.

Controversial arrangements at the centre 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 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 seemingly less rigid, as they allow sellers to lower prices on rival platforms and offline but not through their website.

Platforms affirm that PPCs are necessary to prevent showrooming, where consumers initially browse the platform to identify their preferred seller but then switch to the seller's direct channel to obtain a discount. This practice, if widely adopted by consumers, could render platforms' activity unprofitable, possibly undermining their existence. PPCs make free-riding unlikely as consumers cannot find lower prices elsewhere. Another important argument presented by platforms in defence of PPCs is that showrooming may undermine their incentives 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 maintaining 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 ability of dominant platforms to charge excessive commissions.

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, the Macron Law, which was adopted on 9 July 2015 and promulgated on 6 August 2015. Our unique and comprehensive dataset covers three years, from June 2014 to May 2017, and includes monthly transaction data for 166 hotels affiliated with three of the top 10 hotel groups operating in Europe and worldwide. These hotels span 61 cities in seven European countries and employ multiple channels to sell their rooms. Among these channels are major OTAs, representing approximately 18% of room nights booked, and the hotels' websites, accounting for about 17%. Interestingly, and perhaps contrary to common belief, the direct offline channel represented the most frequently used booking channel among consumers, accounting for roughly 46% of total room nights booked over our sample period.

The subject of our analysis lies at the forefront of current policy debates. Banning PPCs should enhance competition not only across sales channels but also among OTAs, potentially benefiting both end consumers and hotels. Moreover, the recently implemented Digital Markets Act (DMA) in the EU prohibits all types of PPCs for gatekeepers such as Booking.com. Drawing from our thorough analysis of a similar but smaller-scale legislation, we can identify potential challenges and offer valuable insights for policymakers and industry stakeholders.

Methodology and Results. We employ quasi-experimental methods to empirically estimate the impacts of the full prohibition of PPCs in France on hotel prices and sales shares across various channels. In our design, hotels in France are the treated group, and hotels in other EU countries, where PPCs were still allowed, serve as control units. Our analysis yields three main results.

First, we find that the ban of PPCs had a negative but not significant effect on room prices on OTAs and hotel websites, two online channels where prices are "visible" to everyone. However, a significant 5.3% price reduction was identified on the hotels' primary offline channel, which includes bookings via direct phone calls, emails, or walk-ins. Prices in this channel are usually "non-visible" to outsiders, as hotels process these transactions internally. For a typical transaction in our sample, this translates into a price reduction of about €8.5 per booking in France.

Second, our findings reveal a significant decrease in the share of room 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 4.6%. No statistically significant change was detected in the share of reservations made through the hotels' websites.

Third, for one of the hotel groups that provided detailed data on commission rates, we find a general reduction in average OTA fees in both 2016 and 2017, which was, however, more pronounced in France. Interestingly, the difference in percentage fee reductions between France and the control group is similar to the percentage price reductions on OTAs.

Several factors may explain these findings. On visible channels, hotels seem to refrain from noticeable price differentiation to avoid potential retaliation from platforms. Hunold et al. (2020) demonstrate that OTAs tend to downlist hotels that set lower prices elsewhere, a practice known as "dimming". Peitz (2022) suggests that platforms may adjust their recommendation algorithms to favour hotels with higher conversion rates, as lower conversion rates could signal that hotels offer more attractive prices on other channels. Bar-Isaac and Shelegia (2025) demonstrate that sellers' hesitation to differentiate prices may be linked to the need to maintain a high position in future ranking. Another response by OTAs to the ban of PPCs was the introduction of Preferred Partner Programmes (PPPs), where maintaining price parity became the condition for top placement in search results (Cazaubiel et al., 2021; Tirole, 2023). Either way, OTAs may achieve outcomes similar to PPCs on online channels without formally applying them.

However, since monitoring prices offline is more difficult, hotels in France were able to offer lower rates through their direct non-visible channel. This pattern did not arise in other EU countries, even though major OTAs such as Booking.com and Expedia had switched from wide to narrow PPCs shortly before the Macron Law. In principle, this change could have allowed hotels to lower prices in the offline channel. A possible interpretation of this difference is that consumers in France were more aware of the opportunity to exert additional effort to find lower offline prices, potentially as a result of the broader media coverage of the Macron Law. Consequently, in relative terms, a larger share of bookings shifted offline following the PPC ban, suggesting that hotels engaged in price discrimination.[1] Nevertheless, we do not observe a significant post-policy expansion in total room-night reservations for the French hotels in our sample compared to the control ones.

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 for the population of 3-star to 5-star French hotels within our sampling window. Inspired by recently developed techniques to calculate welfare bounds across consumer groups (Canzian et al., 2024; Kang and Vasserman, 2025), we find non-negligible savings. Over the sampling period of our study, we estimate that

[1] We use the term *price differentiation* when channels entail different costs (e.g., OTAs vs. hotel website), whereas *price discrimination* applies when price differences reflect consumer sensitivity across channels with similar costs (e.g., hotel website vs. direct offline channel).

consumers who booked directly through the primary offline channel that we consider may have saved up to approximately €217 million. However, this amount is relatively small, from an economic perspective, compared to the annual revenue of the entire French hotel sector, which ranged from €24 to €26 billion during the same period (Euromonitor International, 2016).

Our findings are relevant for at least two reasons. First, they suggest that hotel clientele may be segmented, with some consumers willing to exert extra effort to secure better prices by contacting hotels directly. Second, the main pro-competitive effect of the policy reform appears not on OTAs or hotel websites, as much of the economic and policy literature has suggested (see, among others, Edelman and Wright, 2015; Johnson, 2017; Baker and Scott Morton, 2018), but rather on the primary offline channel where consumers can directly contact the hotels. While less visible, this channel accounts for a substantial share of transactions, as noted earlier, and we observe significant price reductions along with increases in its relative sales share. Notably, without access to proprietary data, such effects might remain undetected.

Finally, we would like to highlight the policy implications of our results. Dominant OTAs seem to have found ways to convince hotels to respect price parity for the online prices, even after the legislative ban on PPCs. In this regard, the policy may have been ineffective in achieving its intended objectives, as also suggested by the economically limited implications that we estimated. This challenge extends beyond the lodging sector, as illustrated by Amazon's practice of removing the "Buy Box" option for those products with lower prices offered elsewhere (Hunold et al., 2022; Scott Morton, 2023). In this context, we suggest that additional provisions should be incorporated in regulations aiming at countering the dominant position of large platforms to make the entire market more transparent and competitive.

Institutional Context. The past decade has been characterised by a series of policy interventions against PPCs, especially when they were 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 a price comparison website for insurance due to its use of wide PPCs.

In the lodging sector, 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. However, narrow PPCs raise similar concerns to wide ones, as hotels might maintain price parity to avoid diverting demand from their own commission-free websites to rival OTAs that, although cheaper than the dominant ones, still charge fees.[2] For this reason, some EU countries also prohibited narrow PPCs, starting with France in 2015, and continuing with Germany and Austria in 2016, Italy in 2017, Belgium in 2018, and Switzerland in 2022.

PPCs remain a central issue of interest for policymakers dealing with the challenges posed by dominant digital platforms. 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 the revision of the Vertical Agreements Block Exemption regulation (Marshall et al., 2021). In July 2024, the Spanish Competition Authority fined Booking.com €413.24 million for abusing its dominant position in Spain between 2019 and 2024. The decision followed complaints from hotel associations about a combination of practices, including narrow PPCs and the platform's ability to unilaterally lower hotel prices.

The DMA, adopted by the European Commission in September 2022, includes the prohibition of all types of PPCs whenever gatekeeper platforms are involved, with enforcement starting in March 2024.[3] This prohibition is complemented by provisions aimed at eliminating practices that serve as substitutes for PPCs, such as dimming and other forms of algorithmic manipulations, echoing our policy recommendations.[4] Booking.com's designation as a gatekeeper in May 2024 makes the analysis in this paper particularly timely and relevant.

Structure. The remainder of the article is as follows. Section 2 reviews the related literature. Section 3 presents a simple model to derive predictions about banning PPCs on visible and non-visible channels. Section 4 presents the data and summary statistics. Section 5 outlines the empirical strategy. Section 6 reports the main results on prices, booking shares, and OTA commissions. Section 7 examines the robustness of our findings, while Section 8 explores heterogeneous effects. Section 9 discusses consumer welfare implications, and Section 10 concludes.

2 Related Literature and Contribution

Theoretical papers agree that removing all types of PPCs should lower prices both in direct channels and on OTAs by intensifying inter-channel competition and reducing commission

[2]The report by European Competition Network (2017) confirms that the incentive to price differentiate under narrow PPCs is very limited, as hotels see "no reason to treat [their] OTA partners differently", and do not want "their website to appear as more expensive than the OTAs" (see page 11 of European Competition Network, 2017).

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

[4]See, for example, Article 6.5, which mandates transparent, fair, and non-discriminatory ranking conditions; https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32022R1925.

rates (Edelman and Wright, 2015; Boik and Corts, 2016; Johnson, 2017; Wang and Wright, 2020). Following the contractual change, sellers may indeed renegotiate their agreements with platforms, paving the way for price adjustments. In this respect, chain affiliation, typically linked to stronger managerial organisation (Kosová and Lafontaine, 2012; Hollenbeck, 2017), is expected to confer greater bargaining power in negotiating commission rates with platforms.

Theoretical findings on narrow PPCs are less clear-cut, as these clauses may represent a compromise between increasing competition in the sector and rewarding OTAs for the service they provide (Edelman and Wright, 2015). Moreover, when competition across platforms is already in place, narrow PPCs may be necessary for multiple OTAs to coexist, especially if showrooming is a concern (Wang and Wright, 2020).[5] Conversely, Johansen and Vergé (2017) argue that competition remains limited with narrow PPCs, as significant commission cuts would be needed to induce price reductions, which would prove unprofitable for platforms.

Recent empirical contributions do not provide conclusive evidence either, possibly because such studies rely on heterogeneous sample compositions (e.g., chains vs. all hotels), data sources (e.g., transaction vs. offered prices), and methodological designs. On the one hand, Hunold et al. (2018) and Ennis et al. (2023) show that the (partial or full) removal of PPCs increases the likelihood that direct channels feature the lowest price. The former article compares trends in different countries following Germany's ban of all types 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.

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 in 2015. Moreover, Mantovani et al. (2021) examined the effect of the full removal of PPCs in France in 2015 using data scraped from Booking.com's website covering the period 2014–2017 for holiday destinations in France and Italy. They found a significant reduction in the short run for hotel prices on Booking.com for the French destinations, followed by a limited response in the medium run. They also find that chain hotels exhibited a more pronounced price reaction, although weakly significant only in the medium run.

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

[5] Wals and Schinkel (2018) add to Wang and Wright (2020) the possibility that platforms adopt a best price guarantee (BPG), and show that BPG strategies, when combined with narrow price parity clauses (PPCs), can serve as a substitute for wide PPCs in deterring the entry of a less efficient potential entrant.

past years on hotel prices. It has been argued that the prohibition of PPCs may have favoured more organised units, such as chain hotels, whereas small and independent hotels may have found it more difficult to break free from the influence of dominant platforms. Our findings reveal that the difficulty in taking advantage of the policy change may be widespread, with only consumers booking directly offline benefiting from lower prices.

This article reports novel empirical estimates of the 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 three ways. First, we leverage a uniquely detailed proprietary dataset with channel-level transaction information from three major global 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 that a specific channel (e.g., the official website) offers the lowest price. Hence, we are the first to study the effects of the prohibition of PPCs on *both* prices and sales channel shares. Third, we exploit partial yet unique information regarding OTA rates to associate the price changes with potential rate reductions following the policy intervention. We also provide consumer welfare bounds for our results (Canzian et al., 2024; Kang and Vasserman, 2025).

Overall, Mantovani et al. (2021) is the closest article to ours, as it exploits the same policy change. The authors gathered web-scraped prices posted on Booking.com by lodging establishments located in Sardinia and Corsica, two islands in geographic proximity and with similar characteristics. Additionally, their sample includes a larger number of lodging establishments across both islands, supporting the internal validity of their study. Our study, covering hotels in 61 cities and resort destinations across seven EU countries, is less geographically focused but offers broader insights at the EU level. Mantovani et al. (2021) find price decreases for rooms posted on Booking.com by hotel chains one year after the Macron Law, albeit weakly significant. Conversely, we find reductions that are not statistically significant in the transaction prices observed on the OTA channel, which includes, however, all intermediary platforms.

We emphasise that the data used in this study are proprietary and cover sales on *all of the hotels' channels*. Notably, our data shows that OTAs accounted for less than 20% of room night sales during the study period, with a similar share for the hotel website. On these visible channels, we find results partly in line with the previous literature: prices on OTAs decrease, but less than those on the hotels' websites. However, these effects are rather small and not statistically significant in our analysis. Importantly, having data from all sales channels allows us to shed light on the less monitored ones, including the direct offline channel, which accounted for almost half of total sales and has been largely overlooked in previous literature and policy discussions. Indeed, we show that the most significant *price and sales effects* occurred in the primary *offline* channel. Furthermore, we employ recently developed estimation methods that leverage machine learning techniques. This allows us to enhance our empirical estimates and demonstrate the robustness of our main findings.

Our work also adds to the recent empirical evidence on the impact of regulation on online platforms, including Facebook (Benzell and Collis, 2022), Instagram (Ershov and Mitchell, 2025) and Amazon (Gutierrez, 2022). Recent articles provide evidence related to the EU's DMA restrictions on, for example, the ban on self-preferencing (Farronato et al., 2023; Reimers and Waldfogel, 2023 and Chen and Tsai, 2024) and search engine defaults (Decarolis and Li, 2023; Decarolis et al., 2025). Complementary to our reduced-form design, Lasio et al. (2025) develop a structural model using similar data and simulate commission rate caps and DMA-style disintermediation, highlighting how different levers shift sales and margins across channels.

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, 2025; Tirole and Bisceglia, 2023; Wang and Wright, 2025) 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 digitisation are fairly distributed and shared among all stakeholders.

3 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 stylised 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 direct offline channel, encompassing hotel direct bookings via emails, calls, and walk-ins. As previously discussed, prices for the first two channels are publicly visible, whereas those for the third are not. While selling through any channel requires no direct cost, transactions on o require hotels to pay OTAs a commission rate, f_o. This rate is set through bargaining between OTAs and hotels, after which hotels set prices across all channels.

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), Karle et al. (2020), and Calzada et al. (2022), inter alia. In this system, each hotel and sales channel pair represents a differentiated product, and 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.

In particular, we define the demand system as follows:

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

where D_{ij} is the demand faced by hotel i on channel j, with p_{ij} representing the price of the room in hotel i purchased through channel j, and $\mathbf{p_{-ij}}$ the vector of prices for all other hotel-channel pairs. Parameter α is the demand intercept, while β_0 and β_1 capture the sensitivity of the demand to a hotel's own price and to the prices of other channels and competing hotels, respectively. The key parameter τ_m measures the difference in price sensitivity of consumers using channel m, which remains non-visible to outsiders, and $\mathbb{1}_m$ is an indicator function that switches on when the channel is m and PPCs are banned. This higher price sensitivity may be related, for example, to the consumers' willingness to exert the additional effort of writing an email or calling the hotel when PPCs do not apply. Additional details on the model and its analyses are provided in Appendix A.

We begin by considering a situation in which the policy change does not affect the commission rates, which are taken as given. The prohibition of PPCs increases competitive pressure across channels by allowing hotels to engage in price discrimination. In equilibrium, prices may adjust differently across channels, as PPCs create an averaging effect between consumer segments with varying price sensitivities. For example, OTA booking prices may rise relative to the case in which PPCs are enforced, whereas prices on the hotel's direct channels, both visible and non-visible, decrease. We also identify cases where the removal of PPCs leads to a decrease in prices across all three channels compared to the price with PPCs, denoted as p^*.[6] In particular, we can identify the threshold value $\hat{\tau}_m$ above which competition across channels is sufficiently

[6]Indeed, PPCs typically stifle price competition across channels because all prices for a room need to be the same. A hotel selling through a lower-cost channel cannot pass on those savings to consumers in the form of lower prices without also reducing the room price on OTAs, which charge higher commissions (Scott Morton, 2023).

intense to reduce all prices after the removal of PPCs:

$$\hat{\tau}_m = \frac{2f_o(\beta_0+\beta_1)[\beta_1(2f_o-7)+2\beta_0]}{\beta_0\left[\beta_1(3+2f_o)(2-f_o)+\beta_0(6-8f_o)\right]}. \tag{2}$$

Moreover, we can compare equilibrium prices across channels once PPCs are banned. If consumers using channel m, which remains non-visible to outsiders, are more price sensitive ($\tau_m \geq 0$), the price on this channel will be lower than on the hotel website: $p^*_m \leq p^*_w$. Moreover, OTAs' commission rates, f_o, effectively raise the marginal costs for hotels, resulting in a higher equilibrium price for OTAs than on the hotel website: $p^*_w < p^*_o$. Absent any price restriction due to PPCs, we thus obtain $p^*_m \leq p^*_w < p^*_o$.

Suppose now that the removal of PPCs strengthens hotels' bargaining power *vis à vis* OTAs when setting commission rates. This may occur because price differentiation allows hotels to shift demand away from platforms to other channels.[7] In this case, the equilibrium commission rate f_o may decline, reducing the cost of using OTAs for hotels, making it more likely that this lower rate translates into a lower room price on the OTA compared to the price with PPCs.

These findings are illustrated through the numerical simulations reported in Table 1, which are based on the demand system (1) for a market with two hotels. All main parameters of the model and their values are reported in the note to the table, as well as in columns (1) and (2).

The equilibrium prices per channel can be found in columns (3) to (5), with one row for the scenario with PPCs (with p^*) and the next for the scenario without PPCs. These prices highlight the crucial role of the threshold $\hat{\tau}_m$, defined in expression (2) and shown in column (6). As an illustration, suppose that the commission rate remains unaffected by the policy change, with $f_o = 0.15$ both in the presence and in the absence of PPCs (Panel A). This yields a threshold $\hat{\tau}_m = 0.033$. When the price sensitivity of consumers on the non-visible channel is relatively low (below the threshold, e.g., $\tau_m = 0.025$), the price with PPCs lies between the prices without PPCs: $p^*_m < p^*_w < p^* < p^*_o$. If, instead, consumers on this channel are more price sensitive (above the threshold, e.g., $\tau_m = 0.05$), then all prices decrease following the removal of PPCs: $p^*_m < p^*_w < p^*_o < p^*$.

Also note that the threshold $\hat{\tau}_m$ increases with f_o, suggesting that a potential reduction in the commission rate after the removal of PPCs would expand the parametric region where all prices decrease. This is illustrated in Panel B for the case where $f_o = 0.11$ after the ban of PPCs,

[7] We provide evidence in this direction in Section 6.2.

Table 1—Simulated Prices With and Without PPCs.

	(1) f_o	(2) τ_m	(3) p^*_m	(4) p^*_w	(5) p^*_o	(6) $\hat{\tau}_m$
Panel A. Fixed f_o						
PPCs	0.15	0.025	202.0	202.0	202.0	0.033
No PPCs	0.15	0.025	191.1	195.0	203.7	0.033
PPCs	0.15	0.050	202.0	202.0	202.0	0.033
No PPCs	0.15	0.050	182.8	190.3	198.8	0.033
Panel B. Varying f_o						
PPCs	0.15	0.025	202.0	202.0	202.0	0.033
No PPCs	0.11	0.025	191.4	195.3	201.5	**0.023**
PPCs	0.15	0.050	202.0	202.0	202.0	0.033
No PPCs	0.11	0.050	183.1	190.6	196.6	**0.023**

Note: The table shows results for $n = 2$, $\alpha = 100$, $\beta_0 = 1$, $\beta_1 = 0.215$, and $\tau_m = \{0.025, 0.050\}$. Examples 1 and 2 (Panel A) assume $f_o = 0.15$, while Examples 3 and 4 (Panel B) use $f_o = 0.15$ when PPCs are present and $f_o = 0.11$ when PPCs are banned.

which leads to $\hat{\tau}_m = 0.023$. Here, for $\tau_m = 0.025$, all prices decrease following the removal of PPCs: $p^*_m < p^*_w < p^*_o < p^*$, whereas with $f_o = 0.15$, this outcome does not occur.

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

Theoretical Prediction 1. *For given OTAs' commission rates, there exist parameter regions where, at equilibrium, the price under PPCs exceeds the prices of all other sales channels once these clauses are prohibited: $p^* > \max\{p^*_o, p^*_w, p^*_m\}$. Moreover, if the OTAs' rates were to decrease at equilibrium following the removal of PPCs, this result would hold in a wider parametric region.*

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 Data

Our empirical analysis leverages transaction data, originally provided to the European Commission by a hotel category association, covering 166 individual hotels across 61 cities in 7 European countries. These hotels are affiliated with 18 chain brands belonging to three of the top 10 largest international hotel groups operating in Europe and worldwide. Our sample covers three years, from June 2014 to May 2017.[8] An observation in the data is a unique hotel-

[8]Our data do not allow us to clearly identify establishment entry or exit over the sample period.

month-channel combination. Each observation features the number of bookings made, the total room nights booked through that channel, and the revenue generated.

From these data, we were able to calculate the average price per room night for each channel-month and the total room nights booked per hotel-month. Room night is a standard statistical metric in the hotel industry. At the hotel level, further information is available about the star rating, the capacity (number of hotel rooms), the review score on OTAs, and additional hotel features and amenities (e.g., whether there is an in-house restaurant, bar, or spa, etc.).

This study focuses on three channels: two online – Online Travel Agency (OTA) and Official Website (WEB) – and one offline, Direct Offline (INN), which includes bookings made through direct phone calls, emails, and walk-ins. These channels are directly or indirectly 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 2 presents the summary statistics for the main variables in our dataset, providing information for each individual country as well as overall. Notably, during our sample period, France (11 cities) experienced the relevant policy change. Hotels in the remaining six countries (50 cities) serve as control units. On average, the hotels in our sample have 4.0 stars and a capacity of approximately 192 rooms. Review scores are very similar, with an average of 8.4 on OTAs. Each hotel sold approximately 3883 room nights per month, with an average room price of 146.6 EUR. Additionally, note that prices in France are higher than the sample average.[9]

Finally, to provide general information regarding the hospitality sector and to study the consumer welfare implications of our findings, we also collect data on the population of French and European hotels from several sources, including France's National Institute of Statistics and Economic Studies (Insee) and Directorate General for Enterprises (DGE). We additionally exploit Google Trends data to analyse the level of attention raised by the policy changes.

[9] The table also shows that hotels in the UK are somewhat different from the rest in terms of capacity as well as occupancy rate. Despite this, we believe all countries should be included to preserve the quality of our control sample. Indeed, hotels in the UK represent a substantial share of our control group (about one-quarter of the total observations). Moreover, both the British and French markets are dominated by large hotel groups, similar to the ones analysed in our study. Finally, as we explain in the following pages, our preferred estimation method exploits the richness of information in the control sample to recover counterfactual outcomes via matrix completion.

Table 2—Summary Statistics of Hotel Characteristics By Country

	Star Ratings	Hotel Capacity	Review Score	Occupancy Rate	Average Price	Room Nights
France	4.1	166.2	8.3	0.60	189.4	3110
(c = 11, N = 23, n = 4438)	(0.6)	(102.6)	(0.5)	(0.16)	(67.3)	(1102)
Control	3.9	196.3	8.4	0.67	139.7	4008
(c = 50, N = 143, n = 26521)	(0.6)	(132.8)	(0.4)	(0.16)	(44.7)	(1346)
Belgium	3.6	160.3	8.3	0.62	119.4	3026
(c = 7, N = 18, n = 3171)	(0.6)	(87.6)	(0.3)	(0.15)	(24.4)	(985)
Italy	4.0	192.3	8.3	0.62	137.8	3550
(c = 11, N = 32, n = 5799)	(0.5)	(111.4)	(0.3)	(0.18)	(49.2)	(1545)
Netherlands	4.1	191.7	8.5	0.69	171.9	4070
(c = 7, N = 21, n = 4114)	(0.7)	(102.5)	(0.4)	(0.15)	(57.1)	(1204)
Portugal	4.1	161.4	8.4	0.64	117.5	3147
(c = 4, N = 16, n = 3001)	(0.7)	(53.9)	(0.4)	(0.19)	(57.8)	(1213)
Spain	3.8	170.5	8.2	0.67	109.8	3264
(c = 11, N = 22, n = 3903)	(0.7)	(95.4)	(0.3)	(0.17)	(34.8)	(1277)
United Kingdom	3.9	254.9	8.5	0.75	162.2	5806
(c = 10, N = 34, n = 6533)	(0.6)	(203.8)	(0.4)	(0.12)	(38.1)	(1489)
Overall	4.0	192.1	8.4	0.66	146.6	3883
(c = 61, N = 166, n = 30959)	(0.6)	(129.2)	(0.4)	(0.16)	(48.5)	(1315)

Note: This table reports the mean hotel characteristics of each country, as well as the overall sample. Standard deviations are reported in parentheses. France is the only country that experienced the treatment, which occurred in Month 15 (August 2015). The hotels in other countries serve as control units. The number of cities is denoted using lowercase c, number of hotels is indicated using uppercase N, and observations are denoted using lowercase n. "Star Ratings" reports each hotel's average number of star ratings. "Hotel Capacity" denotes the average number of rooms per hotel. "Review Score" reports each hotel's static average review score displayed on OTAs. "Occupancy Rate" denotes the average occupancy rate. The "Average Price" column reports the average price per room sold in each hotel. "Room Nights" indicates the average monthly room-night sales of each hotel.

5 Empirical Strategy

We exploit a major legislative change in the European hospitality sector to provide evidence on the effects of prohibiting PPCs. On 6 August 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. 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 direct offline channel than in the visible direct online channel and the OTA channel, respectively (Theoretical Prediction 2). As our dataset contains finalised transactional information for each booking channel per month, we explore the effects of the legislation on hotel prices and room sales across the three channels.

For our difference-in-differences (DID) 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. These countries are in the same economic and geographic area, and are therefore very similar from an institutional viewpoint and subject to similar economic shocks.

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

$$Y_{it} = \delta_i + \gamma_t + \tau^{\text{TWFE}} D_{it} + \varepsilon_{it}, \tag{3}$$

where i identifies a unique hotel-channel combination, and t denotes the month. The main 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 average monthly 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-channel (unit) fixed effect, and γ_t is a year-month 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 four main assumptions. First, we assume that only French hotels received a major exogenous "shock" – the Macron Law. However, due to the Paris terrorist attacks on 13 November 2015, which was a persistent and negative demand shock to accommodations in Paris (Insee, 2016, Table 1), our main specifications focus on estimates that exclude hotels in the French capital. As the Macron Law and the terrorist attacks in Paris are relatively close in time, it would be challenging to isolate the price effects of one event from those of the other. Regarding the hotels in the control group, we assume that they were not exposed to any exogenous shocks.

Second, we assume that there are no anticipation effects in the pre-treatment periods. However, regulatory interventions are typically announced before they are implemented, and the Macron Law coincided with other developments related to PPCs in Europe, such as the shift from wide to narrow PPCs. In Section 7, we therefore formally address several timing-related issues and provide further robustness checks.

Third, we assume that the prohibition of PPCs in France did not affect the pricing of hotels in the control group. In other words, we rule out potential spillover effects of the Macron Law, which could have led to anticipatory behaviour in the control countries, especially those where discussions about banning PPCs were ongoing. For example, Italy and Belgium, which are part of our control group, indeed banned PPCs, but only after the end of our data period.

Fourth, 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 of the control group (parallel trends). To gauge evidence for this assumption, we employ the following *event study* specification:

$$Y_{it} = \delta_i + \gamma_t + \sum_{t=-14,\, t\neq -1}^{21} \beta_t M_{it} + \varepsilon_{it}, \tag{4}$$

where δ_i is the hotel-channel 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_{-14} to β_{-2} regarded as the "pre-trends" and β_0 to β_{21} interpreted as the dynamic path of the ATT. The error term is ε_{it}. By convention, the coefficient of period -1 is normalised to 0.

Finally, to tackle the well-known issues of biased standard errors in DID models (Bertrand et al., 2004), we follow Angrist and Pischke (2008) and Abadie et al. (2023) and cluster the standard errors at a higher level of aggregation, namely, the city.

Matrix Completion–Nuclear Norm (Athey et al., 2021). To strengthen our analysis, we also employ the Matrix Completion–Nuclear Norm (MC-NN) estimator. MC-NN originated in forecasting tasks in Computer Science and adopts machine learning techniques to impute missing potential outcomes in panel data by solving a convex optimisation problem. Specifically, it estimates a low-rank matrix that best fits the observed outcomes while penalising complexity via the nuclear norm. The estimator learns latent patterns from pre-treatment outcomes across all units, which it then uses to predict the missing counterfactuals. The ATT is computed as the difference between the observed outcomes and the imputed counterfactuals for treated units.

Unlike traditional estimators such as TWFE, which rely on strong parametric assumptions, MC-NN is flexible and data-driven. Different from synthetic control methods (Abadie, 2021), it does not construct counterfactuals as weighted averages of control units, nor does it require exact matching of pre-treatment trajectories. Compared to matching estimators that select subsets of control units based on observable similarity (Abadie and Imbens, 2011), MC-NN leverages the entire data structure across all units and time periods to recover missing counterfactuals. These features make MC-NN particularly well-suited in our context, as hotel data exhibit high volatility and strong seasonal cycles. In our application, MC–NN smooths seasonal patterns more effectively and yields more stable estimates, leading to modest efficiency gains relative to TWFE.[10]

The main model follows the form:

$$\mathbf{Y} = \mathbf{L} + \Gamma \mathbf{1}_T^\top + \mathbf{1}_N (\Delta)^\top + \varepsilon, \tag{5}$$

where $\mathbf{Y}$ denote $\mathbf{Y} \in \{\mathbf{p}, \mathbf{s}\}$, the complete outcome matrices of the outcome variables. These matrices feature 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-channel fixed effect, and $\Delta \in \mathbb{R}^{T\times 1}$ denotes the time fixed effect. Finally, ε is a random independent error vector. The estimation involves solving:

$$\min_{\mathbf{L},\Gamma,\Delta} \left\{ \frac{1}{|\mathcal{O}|} \|\mathbf{P}_{\mathcal{O}}(\mathbf{Y} - \mathbf{L} - \Gamma \mathbf{1}_T^\top + \mathbf{1}_N (\Delta)^\top)\|_F^2 + \lambda_L \|L\|_* \right\}, \tag{6}$$

[10] As a robustness check, we also employ a Nearest Neighbour Matching estimator (Deryugina et al., 2020).

where $\mathcal{O}$ denotes the number of the outcomes, and $\mathbf{P}_{\mathcal{O}}(\cdot)$ represent a partition of such a matrix. Calculating the estimator involves matrix shrinkage and the scalar associated with the penalty term, λ, which is optimally selected through a ten-fold cross-validation process. Inference is performed via a clustered non-parametric bootstrap procedure. The estimation procedure is implemented through the *gsynth* package in R provided by Xu and Liu (2022).

6 Market Effects of Prohibiting PPCs in France: Prices and Sales

6.1 The Macron Law: Effects on Prices

The estimated TWFE coefficients are reported in Table 3, 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 prices on these two channels are posted on their respective websites, making them 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 in France. The estimated coefficient for hotel websites (WEB) shows 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 previously discussed, the reservations for this channel are made through emails, phone calls, and walk-ins. As such, the prices for these bookings are typically not visible to parties not involved in the transactions. The TWFE coefficient indicates a difference of -5.656% for INN, which translates into approximately €8.5 per booking in France. Compared to the online channels, the offline channel experienced a much larger and statistically significant price decrease. Finally, Column (4) reports the overall effects of the Macron Law on French hotel prices, estimated using data from all sales channels. The estimated coefficient τ^{TWFE} indicates an overall price effect of -3.490%, which is, however, only weakly significant at the 10% level.

In Panel B, the estimations are performed using the MC-NN method developed by Athey et al. (2021). The results qualitatively confirm those obtained in Panel A. The only difference is that the impact on the prices on all channels is not significant. We also note that the estimated coefficients of both panels are quantitatively similar, vouching for the robustness of our results.

Panels A and B also report the RMSEs (root mean squared errors) of both estimators. The RMSE measures the average deviation between observed and predicted outcomes, with lower values indicating a better fit. Across all columns, MC-NN consistently achieves lower RMSEs

Table 3—Effects of Prohibiting PPCs: Prices

	Dependent Variable: Log Price × 100			
	OTA (1)	WEB (2)	INN (3)	All (4)
Panel A. TWFE-DID Estimates				
τ^{TWFE}	−1.680	−2.004	−5.656***	−3.490*
	(2.477)	(2.348)	(2.074)	(1.960)
RMSE	18.881	19.630	19.618	21.789
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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. MC-NN Estimates				
$\tau^{\text{MC-NN}}$	−1.384	−1.780	−5.343***	−3.235
	(2.628)	(2.413)	(2.170)	(1.987)
RMSE	15.276	18.346	15.959	18.580
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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: The 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 Equation (3). Panel B reports the MC-NN estimates using Equation (5). RMSE denotes the estimated root mean squared errors. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

than TWFE. These improvements led us to adopt MC-NN as our preferred estimation technique for subsequent robustness checks and heterogeneity analyses.

To offer visual evidence that the parallel pre-trends assumption is satisfied for our analyses, we present the estimated dynamic ATTs in Figure 1. These results are obtained by estimating Equation (4) using MC-NN. For each graph, the vertical axis plots the percentage price changes, whereas the horizontal axis plots the months. The vertical bar at "Aug-2015" indicates the Macron Law. Panels A to D plot the percentage price differences of French hotels versus counterfactual French hotels, for the four channels corresponding to Table 3.

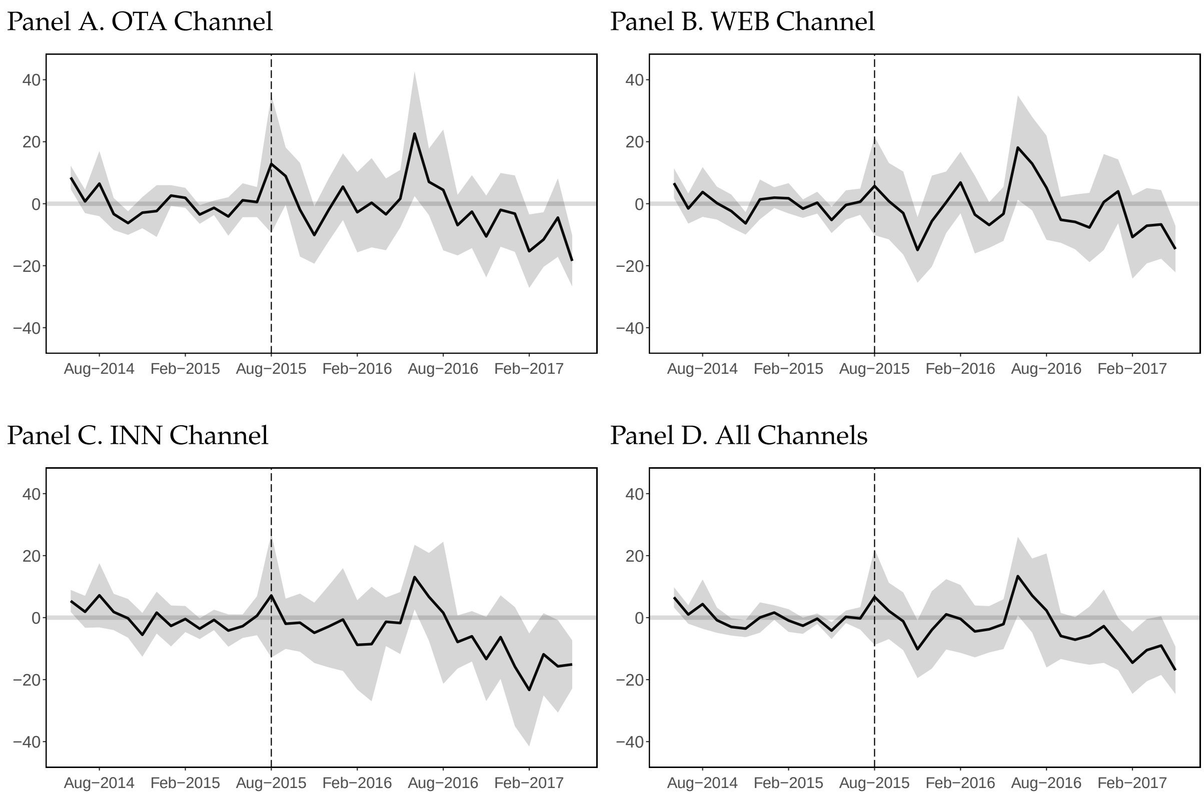


Figure 1: MC-NN Analysis of Log Price — France and Counterfactual France

Examining the trends of percentage price differences before the promulgation of the Macron Law, we note that the pre-trends are relatively stable and, with rare exceptions, not significantly different from zero. This suggests satisfactory pre-treatment parallel trends and attests to the suitability of our control group and empirical strategies, particularly considering the span and diversity of our sample. The post-treatment periods confirm the mostly negative impact of the prohibition of PPCs, particularly on the INN channel. The figures also indicate a delay between the policy implementation and when the price effects materialised. We further discuss the timing of these effects in Section 6.3. We also present similar event study plots estimated using the TWFE specifications in Appendix C (see Figure C.1), which are similar to Figure 1 but more volatile due to the relative inefficiencies of the TWFE estimator.

Our first set of findings reveals an interesting picture. As noted above, most policymakers and researchers expected a significant price drop following the prohibition of all PPCs, especially on the direct online channel. In our sample, prices did decline after the Macron Law, as indicated by the negative signs in Table 3, and the decrease was greater for WEB than for OTAs. Nonetheless, neither the coefficient for OTA nor WEB is significantly different from zero, and the difference between the two coefficients is not statistically significant. Thus, Theoretical Prediction 1 is only partially confirmed. However, we observe a significant price decrease on the main non-visible offline channel (INN), supporting Theoretical Prediction 2 and suggesting that hotels in France offered better deals to customers booking through this channel after the ban.

Finding 1. *The prohibition of PPCs in France led to negative but not statistically significant price effects on French hotels' visible online channels* (*OTA and WEB*)*. In contrast, a larger and statistically significant negative effect* (*-5.343%, according to our preferred specification*) *was observed for prices on the non-visible direct offline channel* (*INN*)*.*

Our results show that significant price effects occurred in INN, the hotel's direct channel not monitored by OTAs. The other direct channel, WEB, did not experience a significant price decline. We believe that an important reason was the potential observability of such a channel by OTAs. Hence, price discrimination was adopted for the channel that was less likely to incite retaliatory responses by the platforms. In particular, practices such as the previously explained dimming (Hunold et al., 2020) may have acted as a deterrent for hotels to price-differentiate on their own websites. In fact, even after the Macron Law, OTAs continued to monitor hotel pricing strategies using rate checker software and contacted them regarding any eventual parity violations (anecdotal examples are provided in Appendix D). Our interpretation is, therefore, that hotels maintained parity on the WEB channel due to the threat of OTA retaliation, but lowered prices on INN, where monitoring was weaker and consumers were more price-sensitive.

Moreover, platforms reinforced collaborative ties with hotels that respected their provisions, rewarding them with better listings and enhanced services. Booking.com, for example, visibly expanded the services offered to both customers and partner firms, especially between 2015 and 2016.[11] Interestingly, visibility boosters and partner programmes were also introduced by

[11]Specifically, Booking.com offered travellers tools to increase their interaction with hotels, such as the *Booking Messages Interface*, a chat tool released in May 2016 to better connect hotels and travellers, and the *Booking Experiences Tool*, introduced in July 2016, which allows users to browse a full list of activities and book tickets in advance. Another important online feature was added in 2016, as indicated by Mantovani et al. (2024): a hotel room was not only indicated as discounted, but the website started to include both the full price, crossed out in red, and the discounted

major OTAs starting in 2015, although we cannot determine how many hotels in our sample participated in these programmes or for how long. We further note that participation in an OTA partner programme usually guarantees enhanced visibility in exchange for higher rates and price parity across channels. However, as we will discuss in Section 6.3, OTA rates have not increased after the PPC ban for the two hotel groups that provided us with this information.

Finally, one may wonder whether hotels intensified efforts to steer consumers toward direct channels after the elimination of PPCs. Whereas we do not have direct evidence about these actions, our dataset includes partial information on outcomes such as reservations by loyalty members and bookings with breakfast included, features often used by hotels as promotional tools. An increase in these proxies may indicate that hotels have tried to include these as benefits to attract users to their online and offline channels. We acknowledge that this may not be the case and that any eventual increase in the outcome may instead be driven by unobserved factors.

While we observe no significant change on the INN channel in France, both levers increased notably on the WEB channel (see Table E.1 in Appendix E). This finding is consistent with hotels concentrating non-price promotions on WEB, where OTA monitoring constrained price cuts, while offering price discounts on INN to directly target price-sensitive consumers.

6.2 The Macron Law: Effects on Booking Channel Shares and Room Night Sales

Effects on Shares of Booking Channels. We now examine the effects of the Macron Law on the sales share of each distribution channel. The sales share is calculated as the room nights sold through a given channel divided by the total room nights sold by the hotel in a given month. Compared to alternative variables (e.g., room nights), the channel share is presented as a percentage and is therefore already normalised across hotels and countries. In addition, it is directly proportional to the number of room nights sold through a specific sales channel.

Studying the changes in channel shares allows us to examine whether the hotels in our sample experienced shifts in sales across different channels. Panels A and B in Table 4 report the estimated coefficients for the two chosen estimation methods. Columns (1) to (2) report the estimated effects of the Macron Law on channel shares for OTA and WEB. The TWFE coefficient (τ^{TWFE}) indicates a statistically significant -2.121% change in the share of sales finalised through OTAs after the Macron Law. On the other hand, the estimated coefficient for hotel websites (WEB) is of lower magnitude, -0.864%, and not statistically different from zero.

price with the percentage reduction offered to hotel guests. While offering no real benefit, this design could enhance perceived service quality and boost hotel visibility on the platform.

Table 4—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***
	(0.824)	(0.702)	(1.091)
RMSE	7.288	5.840	11.078
Year-Month FE	✓	✓	✓
Hotel-Channel FE	✓	✓	✓
Sales Share	17.7%	17.0%	45.9%
Observations	5,406	5,418	5,302
No. of Hotels	157	157	156
Panel B. MC-NN Estimates			
$\tau^{\text{MC-NN}}$	−2.149***	−0.890	4.600***
	(0.813)	(0.737)	(1.039)
RMSE	7.070	5.965	10.858
Year-Month FE	✓	✓	✓
Hotel-Channel FE	✓	✓	✓
Sales Share	17.7%	17.0%	45.9%
Observations	5,406	5,418	5,302
No. of Hotels	157	157	156

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 Equation (3). Panel B reports the MC-NN estimates using Equation (5). RMSE denotes the estimated root mean squared errors. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Interestingly, whereas we did not find statistically significant price decreases on either of these online channels (see Section 6.1), there was a relative decrease in the number of transactions finalised through OTAs. Analysing the price effects of the legislation in isolation would overlook changes in sales shares and, as a result, the overall effects of the policy may be misestimated.

Column (3) reports the estimated effects on the sales shares of the non-visible INN channel. Compared to the visible online channels, information regarding the prices or quantities (such as the number of available rooms) of the direct offline channel cannot be directly observed or retrieved by web scraping. Nonetheless, this channel constitutes a substantial share of the total room nights sold by hotels, averaging above 40%.[12]

The TWFE coefficient for INN indicates a significant increase of 4.526% after the Macron Law relative to the control. This substantial increase in the sales share of the main offline channel contrasts with the significant decrease in the OTA channel, and suggests a shift in the rooms sold from OTA to INN. Also, in this case, the estimated coefficients are quantitatively similar across Panels A and B, vouching for the robustness of our results.

Finally, Figure 2 presents the estimated dynamic ATTs.[13] The interpretation of each graph is similar to the graphs in Figure 1, with the distinction that sales share differences, rather than percentage price differences, 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. The post-Macron Law patterns graphically illustrate the results discussed above: a significant shift in sales occurred from the OTA channel to INN. Also, note that this shift took a few months to materialise, with no change in the first few months after the prohibition of PPCs in France.

Finding 2. *The prohibition of PPCs in France led to a significant decrease in OTA sales share for French hotels* (-2.149%) *and a significant increase in INN sales share* (+4.600%). *In contrast, the share of sales through WEB showed no significant change.*

Overall, the following picture emerges. When examining the price and sales effects holistically, we observe a significant sales shift from OTA to INN, but no significant change to WEB. As shown at the end of Section 6.1, hotels focused on attracting consumers to their websites by offering promotional deals. However, the findings in this section suggest that these efforts were largely ineffective. Indeed, consumers appear to respond primarily to price cuts, as evidenced by a significant increase in the sales share of the offline channel, where prices decreased.

[12]See Appendix B for further information on the sales shares of each channel, in particular Table B.1.

[13]Similar event study plots estimated using the TWFE specifications can be found in Appendix C (Figure C.2).

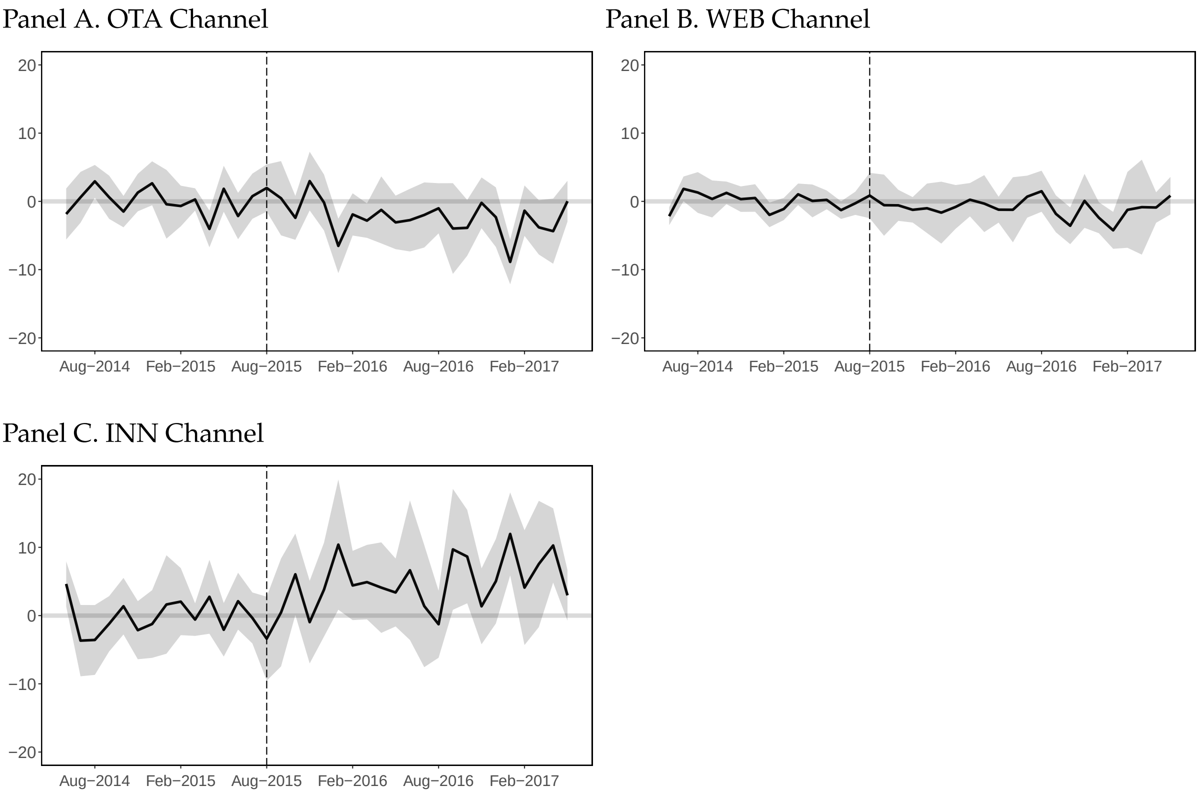


Figure 2: MC-NN Analysis of Channel Shares — France and Counterfactual France

One may wonder why similar effects were not observed in control countries, given that major OTAs had implemented similar commitments in 2015 (e.g., narrow PPCs) at the EU level, which exempted offline channels from parity obligations. It is worth observing that, while the Macron Law had a significant media impact in France, possibly raising consumer awareness and encouraging them to make an effort to book offline, no such effect was observed in the other EU countries, where the switch from wide to narrow PPCs seems to have attracted far less attention. We support this conjecture with evidence from Google Trends (see Appendix F), which indicates that the Macron Law generated substantial interest in both web and news searches in France and beyond. By contrast, the commitments of major platforms such as Booking.com and Expedia to adopt narrow PPCs received relatively little attention. However, we acknowledge that the observed offline price reductions could also be consistent with other supply-side and institutional mechanisms that do not rely on consumer awareness.

Effects on Room Night Sales and Reservations. To complement our analysis of the effects on channel shares, we briefly examine the effects of the Macron Law on room nights booked and the number of reservations made. As noted above, these two measures are highly correlated with channel shares, as the latter is simply derived by dividing the room nights sold through each channel by the total room nights sold by a hotel in a given month.

Table 5 presents the results of the MC-NN analysis, where room night sales and the number of reservations are used as dependent variables. The event study plots can be found in Appendix G (see Section G.2, Figures G.2 and G.3).[14] Similar to the results of channel shares in Table 4, we notice mild reductions in OTA and WEB sales compared to the control group, but an increase in sales through INN, although the changes are mostly weakly or not statistically significant.

Table 5—Effects of the Macron Law on Room Nights and Reservations

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Room Night Sales			
$\tau^{\text{MC-NN}}$	−44.11	−36.11*	117.36*	−6.514
	(30.91)	(21.26)	(61.47)	(17.07)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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
	Dependent Variable: Number of Reservations			
$\tau^{\text{MC-NN}}$	−20.58	−20.16**	103.4***	5.395
	(15.61)	(9.00)	(40.15)	(9.21)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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 effects of the Macron Law on showrooming. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

These results suggest a shift from online sales to direct offline sales, supporting our previous analyses on channel shares. In addition, these identified patterns could potentially be consistent with showrooming. However, as we lack direct evidence on consumers' search behaviour, we cannot take a definitive stance on this interpretation. Other mechanisms may also align with our findings. For instance, an increased price sensitivity induced by the ban of PPCs may have led a subset of consumers to take advantage of the lower prices offered through INN, without necessarily having initially searched on OTAs.

[14] In Section G.1, we also provide descriptive evidence that the hotels in our estimation sample did not experience significant expansions in their sales in the window of observation. The total number of room nights sold remains constant over the years, albeit with seasonal fluctuations.

6.3 Commission Rate Reductions and Price Effects

In this section, we examine the relationship between prices and OTAs' commission rates proposed in Section 3. The data are on the *effective commission rate* (fees paid relative to the value of OTA bookings for each month), which incorporates the contracted baseline percentage plus any adjustments linked to visibility or partner programmes where applicable. We do so by focusing on Hotel Group 1, which provided us with granular data on the OTAs' commission rates for each affiliated establishment.[15]

Figure 3 plots the average normalised OTAs' commission rates for establishments belonging to Hotel Group 1 in France and 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, which most likely resulted from renegotiations between the hotel group and the OTAs. A similar but more moderate reduction can be observed in 2017, closer to the end of our sample period.

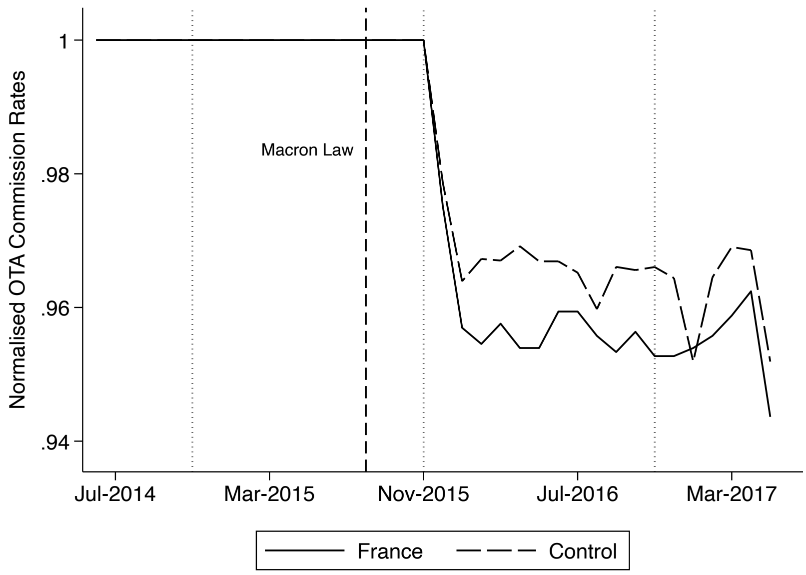


Figure 3: Normalised OTA Commission Rates: Group 1

This common decrease of the OTA commission rates can be related to a number of factors. For example, it may indicate a spillover effect of the Macron Law to other countries, but could also be the result of a downward trend in the industry.[16] It is also worth noting that the commission

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

[16]During those years, hotels were trying to reduce their reliance on OTAs, for example, by trying to attract more clientele to their direct channels through "Book Direct" marketing campaigns. This may have led to a decrease in the effective rates as a result, for example, of reduced spending on ranking-boost or sponsored-placement services. At the same time, large hotel groups were aggressively bargaining to reduce their OTA rates, culminating in the

rate change is not exactly identical for the hotels in the treated and the control group: indeed, the French hotels enjoyed a 1.013% further reduction in 2016 (-4.444%) than their sister hotels operating in the control countries (-3.431%).

In light of the rate decrease in 2016 and the relative difference between treated and control hotels, we now perform the MC-NN analysis on hotels belonging to Hotel Group 1. The estimated coefficients are reported in Table 6, and the estimated dynamic ATT plots, in Appendix I. Although this exercise is only performed on a sub-sample of hotels, the pre-trends of the ATT plots are sufficiently stable, with no noticeable deviations from zero.

Table 6—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 (1.941)	-2.372 (2.542)	-6.016^{**} (2.431)	-3.812^{**} (1.511)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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 for hotels belonging to Hotel Group 1. The analyses use the MC-NN estimator. The WEB, OTA, INN column headers indicate the coefficients estimated using data subsets from the respective channels. The last column reports the estimated coefficients using data from all sales channels. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Focusing on the effects of the PPC ban, we begin with Table 6, Column (1). The reduction in OTA prices for Hotel Group 1 (-1.309%) is similar to the full-sample estimate (-1.680%) in Table 3, Column (1). As in the baseline, the price decrease on OTA for Hotel Group 1 is not statistically different from zero. Moreover, the magnitude of the percentage price estimate is in line with the relative percentage reduction in OTA commission rates for this group, which is around -1.013%, from the data presented in Figure 3.

Finding 3. *The average OTAs' rates for establishments in Hotel Group 1 decreased in 2016 and 2017. The percentage price reductions of French hotels on OTAs after the prohibition of PPCs in France are in line with the percentage reduction in the fees.*

well-known Marriott–Expedia deal. See: https://www.cnbc.com/2019/04/11/after-tense-negotiations-marriott-signs-a-new-multiyear-deal-with-expedia.html. More generally, we note that larger chains, like the ones in our sample, often negotiate rates and conditions with OTAs, while independent hotels have standard contracts. Unfortunately, our data do not allow us to disentangle between these two possible drivers of the decrease in the commission rates, and we acknowledge that both may have played a role.

Taken together, these insights suggest that, despite the bargaining power of this internationally renowned hotel group, its establishments lowered prices only in proportion to the percentage reductions in OTA commission rates when faced with a legislative ban on PPCs. In other words, there seem to have been limited *between-channel* pro-competitive effect of removing PPCs. Any detected effect should be interpreted cautiously given the lack of statistical significance.

Table 6, 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 3, Column (2). The coefficient on INN in Column (3) is -6.016%, which is statistically significant and slightly greater in magnitude than the baseline coefficient (see Table 3, Column (3)). Finally, the price reduction across all sales channels in Column (4) is consistent in magnitude with the baseline results in Table 3, Column (4).[17]

These results on the changes in the OTA rates offer a possible rationalisation for the lagged price effects of the Macron Law identified in Section 6.1. Moreover, these findings are also in line with our theoretical predictions regarding the impact of a decrease in OTAs' rates (see the final part of Theoretical Prediction 1).

We also highlight the link between the theoretical and empirical results. The model's flexibility allows for multiple outcomes that can be mapped onto our empirical findings, with some caveats. In particular, assuming high consumer sensitivity to offline price options, the price reduction observed after the PPC ban aligns qualitatively with the model's prediction, in which direct prices fall below PPC prices. The example in the first two rows of Panel B in Table 1 reproduces a roughly 5% price decline in INN when PPCs are banned, consistent with Finding 1. Price reductions in the OTA channel also align with Finding 3. The only notable discrepancy concerns WEB prices, which fall less in reality than the model predicts. This is because the model does not account for OTAs' threats of retaliation. In practice, hotels kept WEB prices close to OTA levels, whereas the theoretical model, absent PPCs and without retaliation, would predict pronounced reductions of prices on the WEB channel.

[17] The results in terms of the shares of each sales channel, available in Table I.1 in Appendix I, are also in line with the baseline results in Section 6.2.

7 Robustness Checks and Other Major Events

In this section, we address several relevant issues related to our identification strategy and possible threats to it, as well as further tests of the robustness of our results.

First, in Appendix J, we extend our baseline analysis by including the observations from hotels in Paris, which were subject to a severe terrorist attack in November 2015. Including these observations leaves the main findings qualitatively unaffected, but it affects the magnitude of the effects compared to Table 3. Indeed, the estimates presented in Table J.1 suggest that the negative price changes are not statistically significant on the OTA and WEB channels. However, they are larger and statistically significant on the direct offline channel, INN. All the coefficients are larger in magnitude compared to our baseline. This may raise the question of whether the decision to exclude Paris hotels from our sample is well-founded. However, our data clearly show that Paris was significantly affected by the November 2015 attacks, with substantial declines in hotel occupancy rates (Figure J.1), thereby supporting our choice of the baseline specification.

The 2016 terrorist attack in Nice may also have affected hotel demand in France, although it occurred well after the implementation of the Macron Law. In Appendix K, we perform an additional robustness check in which we re-estimate our main specification excluding observations from *both* Paris and Nice. The results are qualitatively similar to those obtained in the baseline.

Apart from these major tragic events, Insee monthly data indicate that hotel room night sales in France follow the expected seasonal pattern and, in the rest of the country, evolve along a broadly stable yearly trend (see Figure G.1, Panels C and D, in Appendix G.1). While some events, such as large sporting or cultural occasions, may cause temporary increases in local demand, our evidence does not point to any sustained structural change in hotel demand in France outside the Parisian region over the period we examine.

Second, as the Macron Law was approved by the French Parliament between June and July 2015, we also consider the possibility of anticipatory and lagged effects in Appendix L. Table L.1 presents the estimated coefficients using MC-NN when the treatment period is shifted one and two months before the Macron Law. This accounts for the OTAs and the hotels' possible anticipation of the policy. Table L.2 presents the estimated coefficients when the treatment period is shifted one and two months after the Macron Law to account for potential gaps between room reservations and check-in. The results are qualitatively and quantitatively similar to our main findings. If anything, our analysis suggests 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 is consistent with our discussion in Section 6.3.

Third, during our study period, high-profile antitrust cases were ongoing in 2014 in Sweden, Italy, and France. These culminated in a commitment by Booking.com and Expedia, Europe's largest OTA platforms, to switch from wide to narrow PPCs in their contracts with hotels in the EU. This was announced in April 2015 and implemented in July 2015. This contractual change allowed sellers to lower prices not only on rival platforms but also on unmonitored channels (such as phone or in-person bookings), provided the prices were not advertised on the hotels' website. Our descriptive data (Appendix M) indicates no visible price changes following the switch from wide to narrow PPCs, with price trends continuing to follow the same seasonal patterns as before between April (announcement) and August 2015 (Macron Law).

Several factors may help explain the price unresponsiveness to the switch from wide to narrow PPCs. For offline prices, as discussed in Section 6.2, the low consumer awareness of this policy change, especially when contrasted with the wider media coverage of the Macron Law, likely played a role in the policy's lack of impact. For online prices, recall that direct bookings do not incur commission fees, whereas OTAs charge a percentage. Consequently, hotels had an incentive to maintain price parity in order to avoid diverting demand from their own website to other platforms, which, although cheaper than the dominant ones, still charged a commission. Policy reports, such as the ones by HOTREC (2015) and European Competition Network (2017), support this view and highlight the limited effectiveness of the 2015 EU reform, an outcome also consistent with theoretical predictions that narrow PPCs do little to change incentives in practice (Johansen and Vergé, 2017; Wals and Schinkel, 2018).

Fourth, we have assumed that the policy did not affect the pricing of hotels in the control group. Whereas we cannot fully rule out the possibility of spillover effects from the French PPC ban on hotel pricing in other countries, our data suggest a seasonal and generally increasing pattern in both the treated and control groups that continued after the implementation of the Macron Law (again, see Appendix M). If spillover effects did occur, though the descriptive evidence seems to suggest otherwise, our estimated price changes would have to be interpreted as a lower bound of the policy effect.

Finally, Appendix N presents two additional robustness checks. First, we provide a more direct analysis of channel price differences using a triple-difference approach. Second, we apply a nearest-neighbour matching approach after performing a seasonal adjustment to the data following Deryugina et al. (2020). Our main results remain robust to these additional checks.

8 Heterogeneity of the Price Effects

Heterogeneity by Pre-Treatment OTA Reliance. A moderating factor influencing price changes could be hotels' relative reliance on OTAs. HOTREC (2020) showed that OTAs' market share in the European hotel sector steadily increased from 19.7% in 2013 to 29.9% in 2019. In our sample, prior to the Macron Law, the mean sales share of OTAs was 19.2%, with a standard deviation of 11.9%, which is slightly below the European average.

On this basis, we define a hotel as having a relatively high reliance on OTAs if its pre-Macron Law OTA sales share exceeds 20%. The idea is that less-reliant hotels may be more comfortable exploiting the pricing flexibility enabled by the PPC ban, while those more dependent on OTAs might be hesitant to raise prices, fearing reduced visibility or performance on the platforms, even in the absence of legal constraints.

We then divide hotels into two categories based on their pre-treatment reliance on OTAs (Appendix O.1). Appendix O.2 provides further details on the MC-NN estimation, as well as ATT plots and estimated effects for both categories. Table O.2 presents the estimated price effects of the Macron Law: Panel A reports results for hotels with a pre-treatment OTA share below 20%, and Panel B for those above 20%. The magnitude of price reductions is consistently larger in Panel A, especially for the direct offline channel (INN) in Column (3), where we find a statistically significant decrease of -6.913%, compared to a non-significant -2.860% in Panel B.

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. Conversely, hotels that were *ex ante* less reliant on OTAs appear to be less affected by any ranking or algorithmic changes imposed by OTAs following a differential pricing strategy across different sales channels.

Heterogeneity by Pre-Treatment Occupancy Rate. Occupancy may also act as a moderating factor, as hotels with relatively high occupancy may be more resilient to shocks from any particular booking channel. Hence, they may be more inclined to experiment and differentiate prices across various channels once PPCs are no longer legally enforced. Provided that occupancy is below full capacity, this can be consistent with offering lower rates or discounts to customers on a particular channel. The occupancy in the hotels of our sample before the implementation of the Macron Law was, on average, 66.2%, with a standard deviation of 15.8%.

Appendix O.3 presents the MC-NN estimation in Table O.3. Panel A shows the estimated price effects of the Macron Law for hotels with an average pre-treatment occupancy below 65%, while Panel B reports the estimates for hotels above this threshold. Overall, price reductions are smaller in Panel A. The differences across Columns (1) to (3) are relevant, amounting to several percentage points per channel. Notably, the only significant estimate in Panel A is the -4.606% change for INN. The estimated price reductions in Panel B, however, are all statistically different from zero, ranging from -3.749% on WEB, -4.959% on OTA, to a pronounced -7.779% on INN. All of these effects are larger in magnitude than those reported in Table 3, Panel B.

Once again, these findings align with our initial expectations. Indeed, hotels with relatively high occupancy rates would be less exposed to booking channel shocks, such as a potential dimming of their search ranking on OTAs. Conversely, hotels with relatively low occupancy rates would more likely suffer from reduced visibility on online platforms.

Heterogeneity by Star Rating. We also examine the heterogeneous responses of hotels with different star ratings, which will also be relevant for the consumer welfare implications in Section 9. We note that traditional hotel segment classifications, or star ratings, tend to correlate with the quality of the hotel. Higher-star hotels typically offer higher quality and cater more to business travellers or less price-sensitive customers, whereas lower-star hotels tend to serve leisure travellers and more price-sensitive segments. As our theoretical model links the expected impact of banning PPCs with the price sensitivity of consumers, it is worth investigating whether the Macron Law had differential impacts on hotels with different star ratings.[18]

Appendix O.4 provides details on the estimation strategy, which, to preserve power, pools observations across all sales channels but subsets the data by hotel star rating. The estimated price effects of the Macron Law by star rating are reported in Table O.4, and Figure O.5 presents the event study plots. On the one hand, the estimated coefficients for 3-star and 4-star hotels are between -2% and -3%, and they are not significantly different from zero. On the other hand, the estimated coefficient for 5-star hotels is around -6.212% and is statistically significant.

These findings suggest that 3- and 4-star hotels were reluctant to lower prices after the Macron Law, possibly due to OTA retaliation. At the same time, 5-star luxury hotels show a larger coefficient than the overall price effect in the baseline model, which was -3.235% (see Table 3, Column (4)). Despite having the least price-sensitive clientele, these findings seem to indicate that luxury hotels are the main drivers of the overall negative price effect.

[18] We note that the hotels in our sample, on average, have relatively high star ratings (4 stars). As a result, one might expect their average consumers to be less price-sensitive, and thus the impact of the PPC ban to be weaker than it would be in the broader hotel population across all quality levels.

The intuition behind these results is that 5-star hotels, the flagship establishments of any hotel chain, tend to attract the most loyal and consistently returning clientele. As a result, these establishments are the least dependent ones (among all star ratings) on OTAs to place their capacity. Moreover, it is likely that the OTAs themselves may wish to maintain cooperation with these hotels to cultivate their presence in the high-end market. Finally, top-tier hotels often attract bookings from corporations or organisations that reserve rooms for short-term conferences or events, potentially benefiting from favourable pricing through the INN channel.

9 Implications for Consumer Welfare

We now try to gauge the potential magnitude of the estimated effects on consumer welfare in France by combining our sample with data on the full population of French and European hotels (2014–2017). We use external sources (DGE and Eurostat) to calibrate our sample to the characteristics of French hotels. However, the resulting welfare estimates should be viewed more as a thought experiment, as we cannot definitively claim that they generalise to all hotels in France. Moreover, these estimates capture only the pure price and quantity effects of prohibiting PPCs. Without further structure, we cannot account for potential changes in room or service quality, search costs, or consumer preferences for different sales channels.

Under these caveats, we adopt an approach inspired by Kang and Vasserman (2025) and similar to Canzian et al. (2024), which estimates consumer surplus using the bounds developed by Varian (1985). This method does not require any equilibrium assumptions regarding firm behaviour or optimal pricing, as would be the case in a structural approach (Canzian et al., 2024). Further details on the external data and the methodological implementation are in Appendix P.

We focus our consumer welfare analysis on INN, which not only shows significant changes in prices and sales shares but also represents 46% of room nights booked in our data. The estimated relative effects for INN were also much larger in magnitude than those for online channels (Table 3). Given that the sales share of INN is approximately the same as the two online channels combined, the overall magnitude for the online channels would also likely be smaller. As a result, by considering only the INN channel, we provide a lower bound for the consumers' gains. Furthermore, since 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, because our sample only consists of hotels rated 3 stars or above, we limit our analysis to French hotels of the same ratings. Although this is a limitation of our approach, it is likely that the relative gains in consumer surplus for lower-rated hotels are smaller, as hotels with one or two stars may have an even higher reliance on OTAs.

To estimate consumer surplus, we leverage the availability of both price and quantity (room nights) data in our dataset, using subscripts 0 and 1 to denote the value of prices (p_0 and p_1) and room nights (q_0 and q_1) before and after the Macron Law. Following Canzian et al. (2024), we estimate the bounds for changes in consumer surplus (ΔCS) of the Macron Law on hotels in our sample, which only assumes that the demand is decreasing in prices:

$$\Delta \text{CS}_{\text{Varian}} \in [(p_0 - p_1)q_1, (p_0 - p_1)q_0]. \tag{7}$$

Table 7 presents the Varian bounds for the relative changes in consumer surplus induced by the Macron Law for the direct offline channel, INN. We focus on hotel categorisation by star ratings, as this is a standard metric in the hospitality industry. Data for the population of French hotels in each category is provided by Direction Générale des Entreprises (2022). The relative gains in consumer surplus are calculated up to May 2017, the end of our sampling period. The Varian bounds are calculated by first estimating the ΔCS for an average hotel of our sample (in each star rating) using Equation (7), then multiplying by the number of hotels (in each star rating) of the entire French hotel sector.

We also account for the differences between our sample and the population by scaling the consumer welfare gains using the ratio of occupancy rates (Eurostat, 2024). The results are expressed in millions of euros. In terms of the population of French 3-star hotels, we estimated that consumers who booked directly saved up to €88.7 million in the 21 months following the implementation of the Macron Law. The corresponding savings for 4-star hotels were up to €55.1 million, and €73.0 million for 5-star hotels. The overall estimates suggest that guests of French hotels may have saved between €180 and €216.8 million in the months following the promulgation of the Macron Law, relative to their counterparts in other EU countries. To put these figures into perspective, we note, however, that the estimated overall annual revenues of the hotel sector in France were approximately €24-26 billion (Euromonitor International, 2016) during the period of our study, indicating that the economic benefits of the policy change were relatively limited.

Table 7—Relative Gains in Consumer Surplus (France)

	Varian Lower Bound (1)	Varian Upper Bound (2)
3-Star	70.0	88.7
4-Star	46.7	55.1
5-Star	63.3	73.0
Overall	180.0	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 Varian (1985) and calculated using Equation (7). The units are millions of euros.

10 Concluding Remarks

In this article, 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 significant policy change, while also examining its impact on the redistribution of sales shares across different channels, as well as on the OTAs' commission fees. We leveraged a unique proprietary dataset of chain hotel prices from 2014 to 2017, including all sales channels.

Our analyses, based on two estimation methodologies, TWFE DID and MC-NN, indicated that the removal of PPCs had negative but not statistically significant effects on room prices posted on OTAs and hotel websites, the visible online channels. However, we identified a significant price reduction on the hotels' main offline channel. In addition, we observed a significant decrease in the sales share of OTAs, accompanied by an increase in the shares of the direct offline channel. These results proved to be robust across various specifications and estimation techniques, including anticipatory reactions and lagged effects of the legislation.

Using granular data from one hotel group in our sample, we also found that a decrease in OTA rates was associated with a comparable, but not statistically significant, percentage reduction in online prices. By contrast, prices on the direct offline channel fell significantly for French hotels within that group.

Our findings reveal the main pro-competitive effect of the policy reform did not materialise on OTAs or hotels' websites, as initially expected, but rather on the main offline channel, where information is exclusively shared between hotels and their clients. This insight is particularly relevant, as it reflects real-world consumer diversity. Especially in digital markets, research should account for this heterogeneity and keep track of the evolving composition of consumers.

In addition, we also estimated the consumer welfare implications of the Macron Law and found substantial savings for consumers who booked directly through the offline channel, adding a quantifiable dimension to the policy's impact. The range of overall savings, relative to their counterparts in the rest of the EU, amounts to hundreds of millions of euros.

One may wonder about the external validity of our findings, in particular, whether significant price reductions occurred in other types of establishments, such as smaller chains or independent hotels. On the one hand, we believe that offering discounts on the direct offline channel to induce a shift in consumer behaviour could also be adopted by these hotels. Applying a discount to phone or email reservations is straightforward and should be feasible even for establishments with more limited managerial resources or simpler organisational structures. On the other hand, smaller chains and independent hotels may face additional challenges that large international groups are better equipped to overcome. First, chain hotels have well-established websites that are easy to find through search engines, giving them demand-side advantages (Hollenbeck, 2017) and reducing their reliance on OTAs. Second, they are generally more agile in sharing information (Baum and Ingram, 1998) and in handling the complexity of price setting (Abrate and Viglia, 2016). Third, chain hotels enjoy stronger bargaining power than independent hotels in negotiating with OTAs and resisting retaliatory strategies (De los Santos et al., 2025). These factors suggest that chain hotels are well-positioned to benefit from the increased pricing flexibility and competition brought about by the PPC ban.

Despite the comprehensive dataset utilised in our analysis, certain limitations were encountered. First, 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 analysing the differential impact of prohibiting PPCs on specific platforms. Yet, it should be noted that, at the time of our analysis, the EU OTA sector was characterised by high concentration: according to HOTREC (2018), as of 2017, 65.6% of all OTA transactions took place on Booking.com. Together with Expedia and HRS, the aggregate market share reached about 86%.

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 market entry and innovative activities carried out by OTAs fall outside the scope of this paper. Moreover, although we extrapolated our empirical findings to the population of 3-star to 5-star hotels in France, we were unable to do so for the unrated, 1-star, and 2-star hotels due to limited quantitative information on how the Macron Law would impact them.

Notwithstanding these limitations, our evidence shows that eliminating PPCs alone did not lead to substantial price reductions in the intended channels. Significant effects emerged only on hotels' direct offline channels, which were not monitored by OTAs, suggesting that practices like dimming may have discouraged price differentiation on hotel websites and OTAs. Moreover, for the channel in which prices significantly declined, our estimates indicate that consumer benefits were modest relative to the overall size of the industry.

Our results suggest that policymakers and antitrust authorities should anticipate how dominant platforms might respond to policy changes aimed at curbing anti-competitive practices. Failing to do so may result in a plethora of interventions that require consistent resources and efforts, without necessarily achieving their policy goals. As discussed in the Introduction, the DMA not only explicitly bans PPCs for gatekeepers but also targets substitute practices, such as algorithmic manipulations, offering a broader set of provisions likely to be more effective than a simple PPC ban in promoting competition across sales channels. However, recent cases, such as the EU non-compliance investigations into Apple and Meta under the DMA, highlight the need for ongoing regulatory and monitoring efforts to safeguard competition in digital markets.

References

Abadie, A., 2021. Using synthetic controls: feasibility, data requirements, and methodological aspects. Journal of Economic Literature 59, 391–425.

Abadie, A., Athey, S., Imbens, G.W., Wooldridge, J., 2023. When should you adjust standard errors for clustering? Quarterly Journal of Economics 138, 1–35.

Abadie, A., Imbens, G.W., 2006. Large sample properties of matching estimators for average treatment effects. Econometrica 74, 235–267.

Abadie, A., Imbens, G.W., 2011. Bias-corrected matching estimators for average treatment effects. Journal of Business & Economic Statistics 29, 1–11.

Abrate, G., Viglia, G., 2016. Strategic and tactical price decisions in hotel revenue management. Tourism Management 55, 123–132.

Angrist, J., Pischke, J.S., 2008. Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Athey, S., Bayati, M., Doudchenko, N., Imbens, G., Khosravi, K., 2021. Matrix completion methods for causal panel data models. Journal of the American Statistical Association 116, 1716–1730.

Baker, J., Scott Morton, F., 2018. Antitrust enforcement against platform MFNs. Yale Law Journal 33, 2176–2202.

Bar-Isaac, H., Shelegia, S., 2025. Ranking algorithms, learning, and pricing. Mimeo .

Baum, J., Ingram, P., 1998. Survival-enhancing learning in the Manhattan hotel industry, 1898–1980. Management Science 44, 996–1016.

Benzell, S., Collis, A., 2022. Regulating digital platform monopolies: The case of Facebook. SSRN Working Paper 3619535 .

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Quarterly Journal of Economics 119, 249–275.

Boik, A., Corts, K., 2016. The effects of platform Most-Favored-Nation clauses on competition and entry. Journal of Law and Economics 59, 105–134.

Calzada, J., Manna, E., Mantovani, A., 2022. Platform price parity clauses and market segmentation. Journal of Economics & Management Strategy 31, 609–637.

Canzian, G., Mazzarella, G., Ronchail, L., Verboven, F., Verzillo, S., 2024. Evaluating the impact of price caps-evidence from the european roam-like-at-home regulation. International Journal Of Industrial Organization , 103115.

Cazaubiel, A., Cure, M., Johansen, B.O., Vergé, T., 2021. Paying for prominence and consumer prices: Evidence from Booking's Preferred Partner Program. Mimeo .

Chen, N., Tsai, H.T.T., 2024. Steering via algorithmic recommendations. RAND Journal of Economics 55, 501–518.

de Cornière, A., Taylor, G., 2019. A model of biased intermediation. RAND Journal of Economics 50, 854–882.

De los Santos, B., O'Brien, D.P., Wildenbeest, M.R., 2025. Agency pricing and bargaining: Evidence from the e-book market. American Economic Journal: Microeconomics, forthcoming.

Decarolis, F., Li, M., 2023. Regulating online search in the EU: From the Android case to the Digital Markets Act and Digital Services Act. International Journal of Industrial Organization 90, 102983.

Decarolis, F., Li, M., Paternollo, F., 2025. Competition and defaults in online search. American Economic Journal: Microeconomics 17, 369–414.

Deryugina, T., MacKay, A., Reif, J., 2020. The long-run dynamics of electricity demand: Evidence from municipal aggregation. American Economic Journal: Applied Economics 12, 86–114.

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.

Edelman, B., Wright, J., 2015. Price coherence and excessive intermediation. Quarterly Journal of Economics 130, 1283–1328.

Ennis, S., Ivaldi, M., Lagos, V., 2023. Price-parity clauses for hotel room booking: Empirical evidence from regulatory change. Journal of Law and Economics 66, 309–331.

Ershov, D., Mitchell, M., 2025. The effects of influencer advertising disclosure regulations: Evidence from Instagram. RAND Journal of Economics 56, 74–90.

Euromonitor International, 2016. EU travel data, retail value RSP, 2005-2014. https://www.euromonitor.com/.

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 URL: https://competition-policy.ec.europa.eu/system/files/2021-07/hotel_monitoring_report_en.pdf.

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.

Ezrachi, A., 2015. The competitive effects of parity clauses on online commerce. European Competition Journal 11, 488–519.

Farronato, C., Fradkin, A., MacKay, A., 2023. Self-preferencing at Amazon: Evidence from search rankings. AEA Papers and Proceedings 113, 239–43.

Gomes, R., Mantovani, A., 2025. Regulating Platform Fees Under Price Parity. Journal of the European Economic Association 23, 190–235.

Gutierrez, G., 2022. The welfare consequences of regulating Amazon. SSRN Working Paper 3965566 .

Hollenbeck, B., 2017. The economic advantages of chain organization. RAND Journal of Economics 48, 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.

HOTREC, 2018. European hotel distribution study 2018. https://www.ghr.fr/IMG/pdf/schegg_2018_european_hotel_distribution_survey_hotrec_france.pdf.

HOTREC, 2020. European hotel distribution study 2020. https://www.hotrec.eu/en/policies/european_hotel_distribution_study_2020_-_summary.html.

Hunold, M., Kesler, R., Laitenberger, U., 2020. Rankings of online travel agents, channel pricing, and consumer protection. Marketing Science 39, 92–116.

Hunold, M., Kesler, R., Laitenberger, U., Schlütter, F., 2018. Evaluation of Best Price Clauses in hotel booking. International Journal of Industrial Organization 61, 542–571.

Hunold, M., Laitenberger, U., Thébaudin, G., 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.

Johansen, B.O., Vergé, T., 2017. Platform price parity clauses with direct sales. University of Bergen Working Papers in Economics 01/17.

Johnson, J.P., 2017. The agency model and MFN clauses. Review of Economic Studies 84, 1151–1185.

Kang, Z.Y., Vasserman, S., 2025. Robustness measures for welfare analysis. American Economic Review 115, 2449–2487.

Karle, H., Peitz, M., Reisinger, M., 2020. Segmentation versus agglomeration: Competition between platforms with competitive sellers. Journal of Political Economy 128, 2329–2374.

Kosová, R., Lafontaine, F., 2012. Much ado about chains: A research agenda. International Journal of Industrial Organization 30, 303–308.

Lasio, L., Ma, J.P., Mantovani, A., Reggiani, C., Duch-Brown, N., 2025. Online travel agencies and beyond: The role of sales channels for hotels and consumers. NET Institute Working Papers 25-07.

Mantovani, A., Piga, C.A., Reggiani, C., 2021. Online platform price parity clauses: Evidence from the EU Booking.com case. European Economic Review 131, 103625.

Mantovani, A., Piga, C.A., Reggiani, C., Shevtsova, Y., 2024. Platform-enabled innovation adoption in the tourism sector: A case study on Booking.com. Tourism Management Perspectives 54, 101316.

Marshall, J., Albrighton, S., Kim, G., 2021. The UK CMA publishes its recommendation for replacing the retained vertical agreements block exemption regulation. https://www.covcom petition.com/2021/11/the-uk-cma-publishes-its-recommendation-for-replacing-the-retained-vertical-agreements-block-exemption-regulation/.

Peitz, M., 2022. The prohibition of price parity clauses and the Digital Markets Act. TechReg Chronicle 1.

Reimers, I., Waldfogel, J., 2023. A framework for detection, measurement, and welfare analysis of platform bias. NBER Working Paper 31766 .

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

Singh, N., Vives, X., 1984. Price and quantity competition in a differentiated duopoly. RAND Journal of Economics , 546–554.

Teh, T.H., Wright, J., 2020. Intermediation and steering: Competition in prices and commissions. American Economic Journal: Microeconomics 14, 281–321.

Tirole, J., 2023. Competition and the industrial challenge for the digital age. Annual Review of Economics 15, 573–605.

Tirole, J., Bisceglia, M., 2023. Fair gatekeeping in digital ecosystems. TSE Working Paper 1452 .

Varian, H.R., 1985. Price discrimination and social welfare. American Economic Review 75, 870–875.

Wals, F., Schinkel, M.P., 2018. Platform monopolization by narrow-PPC-BPG combination: Booking et al. International Journal of Industrial Organization 61, 572–589.

Wang, C., Wright, J., 2020. Search platforms: showrooming and price parity clauses. RAND Journal of Economics 51, 32–58.

Wang, C., Wright, J., 2022. Platform investment and price parity clauses. Journal of Industrial Economics 71, 538–569.

Wang, C., Wright, J., 2025. Regulating platform fees. Journal of the European Economic Association 23, 746–783.

Xu, Y., Liu, L., 2022. gsynth: Generalized Synthetic Control Method. URL: https://yiqingxu.org/packages/gsynth/. R package version 1.2.1.

Online Appendix for "The Price Effects of Prohibiting Price Parity Clauses: Evidence from Global Hotel Chains"

Table of Contents

A The Economic Effects of Removing PPCs: Theoretical Hypotheses

The profit function of hotel i, omitting the arguments in the demand functions for ease of notation, can be written as:

$$\pi_i(p_{ij}, \mathbf{p_{-ij}}) = p_{io}D_{io}(1-f_o) + p_{iw}D_{iw} + p_{im}D_{im}, \tag{8}$$

with demand function D_{ij} specified in (1) for $j = o, w, m$. This demand 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., $|\partial D_{ij}/\partial p_{ij}| > \partial D_{ij}/\partial p_{-ij}$. These assumptions hold, for example, in the demand system by Singh and Vives (1984), as discussed in the main text.

Assume that the commission rate f_o is given. Under this demand specification, the first order conditions (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

$$FOC_p(p, \mathbf{p_{-ij}}) = (3-f_o)\left[\alpha + 3(n-1)\beta_1 p_{-ij} - 2\left(\beta_0 - (n-1)\beta_1\right)p\right], \tag{9}$$

with PPCs, and as

$$FOC_w(p, \mathbf{p_{-ij}}) = \alpha + \beta_1[(4-f_o) + 3(n-1)]p_{-ij} - 2\beta_0 p, \tag{10}$$

$$FOC_m(p, \mathbf{p_{-ij}}) = \alpha + \beta_1[(4-f_o) + 3(n-1)]p_{-ij} - 2\beta_0(1+\tau_m)p, \tag{11}$$

$$FOC_o(p, \mathbf{p_{-ij}}) = \alpha(1-f_o) + \beta_1[(4-f_o) + 3(n-1)(1-f_o)]p_{-ij} - 2\beta_0(1-f_o)p, \tag{12}$$

when PPCs are not imposed by OTAs.

We start by noting from Equation (9) 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 $\beta_0 > (n-1)\beta_1$. Focusing on the FOCs in (10)-(12), we observe that the FOC for channel m decreases faster than that for channel w, as $-2\beta_0(1+\tau_m) < -2\beta_0$. Since the intercept of both FOCs with the vertical axis is identical, we can conclude that the FOC for channel m lies below that for channel w in the first quadrant and, hence, crosses the horizontal axis at a lower price. Therefore, we conclude that $p_m^* < p_w^*$.

Second, the FOC of channel o has a lower intercept with the vertical axis than that of channels w and m. This can be seen by comparing the first two terms on the right-hand side of (12) and of (10) (or (11)), 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 this 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, (9), 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, therefore, possible to know *a priori* whether the FOC under PPCs crosses the horizontal axis at a higher or lower value of p than the other FOC functions. In fact, the price with PPCs, p^*, may be higher than all prices observed when these clauses are absent. At the same time, the price on OTAs may increase following the removal of PPCs, while prices on other channels decrease.

Figure A.1 shows the combinations of the parameters τ_m and f_o where equilibrium OTA prices are higher (dark grey) or lower (light grey) when PPCs are removed, compared with the uniform equilibrium price under PPCs. The two regions are separated by the yellow line, which represents the threshold value $\hat{\tau}_m$ defined in (2). Notice that this threshold is increasing in f_o and does not depend on α; we can also easily verify that it increases in β_0 and decreases in β_1.

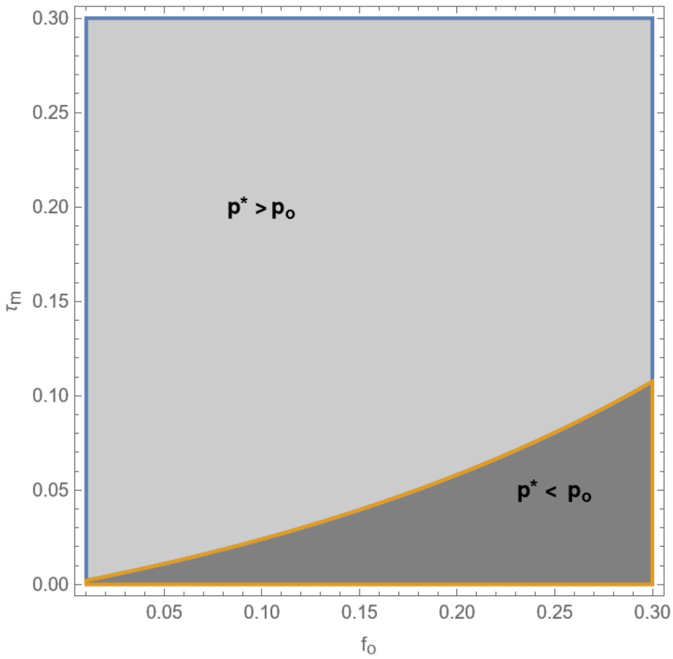


Figure A.1: Uniform Equilibrium Price Under PPCs vs. OTA Equilibrium Price Without PPCs. Example based on: $n = 2$, $\alpha = 100$, $\beta_0 = 1$, $\beta_1 = 0.215$.

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 Official Website (WEB). The OTA channel includes 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 Direct Offline (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 WEB, INN, and CRO channels. The INN channel is the main direct offline sales channel for hotels. It comprises direct phone calls, email reservations, and walk-ins, as described in the main text. The CRO channel includes bookings made by calling the chain-specific call centres. 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 somewhat unique, as the rooms are often offered to travel agencies before the season begins. These rooms may be included in holiday packages or resold to other sellers.

As specified in the main text, our analysis focuses on three distribution channels: OTA, WEB, and INN. The first two should be directly affected by the prohibition of PPCs, whereas the last one should be at least indirectly affected by this policy change. 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 various 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
Online					
[1] OTA (Online Travel Agencies)	15.8	17.4	18.5	19.6	17.7
[2] WEB (Official Website)	15.7	16.3	18.0	18.5	17.0
Offline					
[2] INN (Direct Offline)	48.6	46.7	44.5	43.2	45.9
[1] 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: [1]Platform, [2]Hotel-owned, [3]Chain-owned, [4]Other.

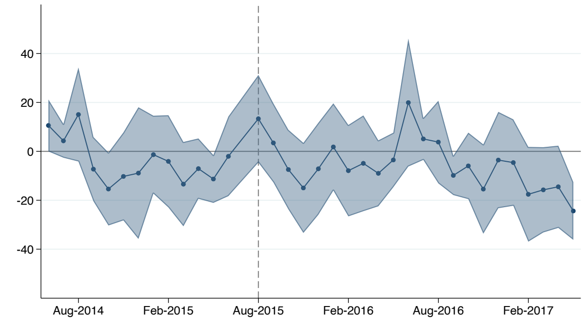
Table B.2—Sales Channel Information For Hotels

Channel	Ownership	Commission Costs
Online		
OTA (Online Travel Agencies)	Platform	High
WEB (Official Website)	Hotel-Owned	Low
Offline		
INN (Direct Offline)	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

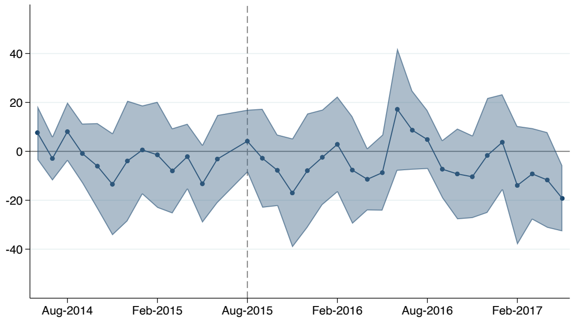
Note: This table summarises the various booking channels available to chain hotels in our sample. The "Commission Costs" column broadly indicates whether the costs of finalising a booking through each channel are high or low for the individual hotels. Information regarding the WHOLESALE and OTHER channels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

C DID Event Study Plots

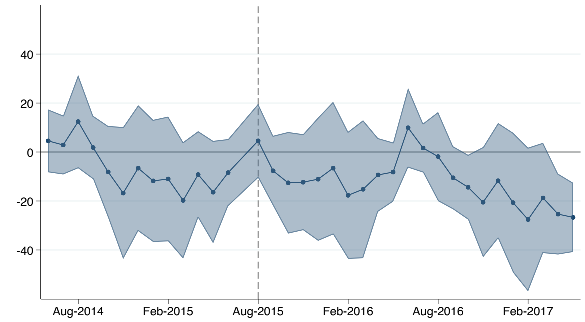
Panel A. OTA Channel



Panel B. WEB Channel



Panel C. INN Channel



Panel D. All Channels

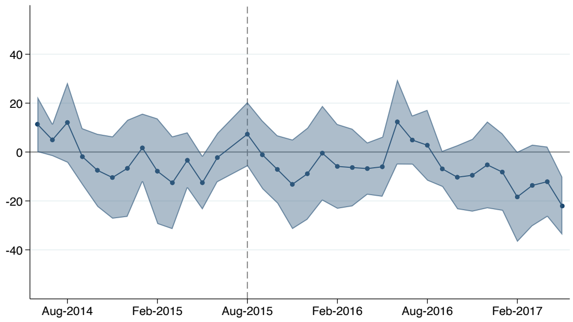
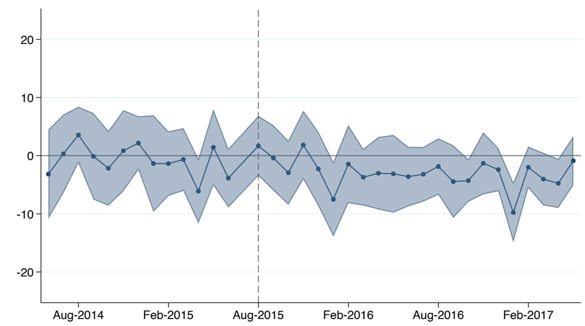
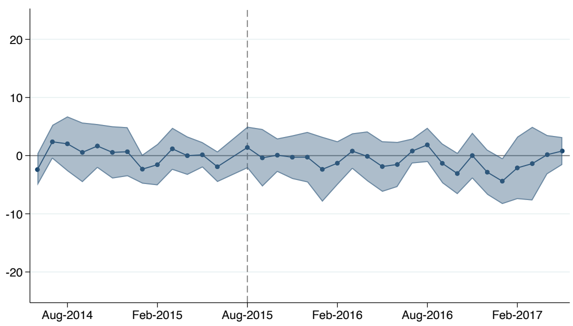


Figure C.1: Event Study for Log Prices — France vs Control

Panel A. OTA Channel



Panel B. WEB Channel



Panel C. INN Channel

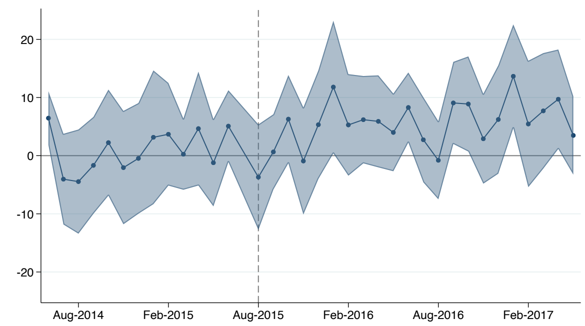


Figure C.2: Event Study for Channel Shares — France vs Control

D Anecdotal Evidence of PPCs and Their Monitoring

This appendix provides anecdotal evidence on PPCs and rate monitoring by OTAs. Figure D.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.

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.

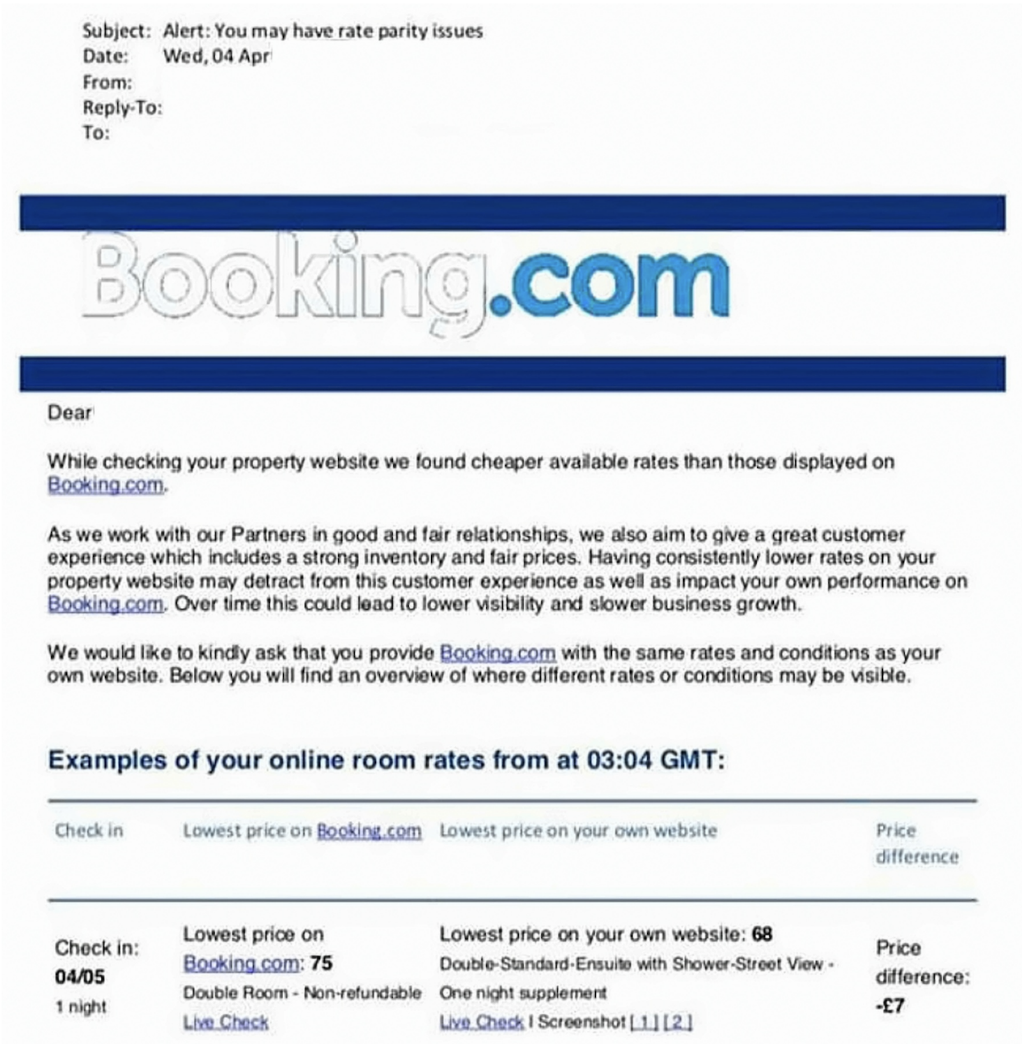
Se dovesse avere dubbi o domande su questa lettera, la invitiamo a contattare Booking.com tramite il suo referente, che sarà felice di assisterla.

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

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

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."

Moreover, there is evidence that OTAs have been monitoring client hotels' pricing behaviour before and after the removal of PPCs. For example, Figure D.2 reports the communication between Booking.com and a client hotel in the UK in March 2020, where narrow PPCs were legally enforced. In the email, Booking.com notifies the client that they have identified a lower room rate available on the hotel's own website.



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

Figure D.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 €122.39 is compared with a Twin/Double Room sold on Booking.com for €95.00.

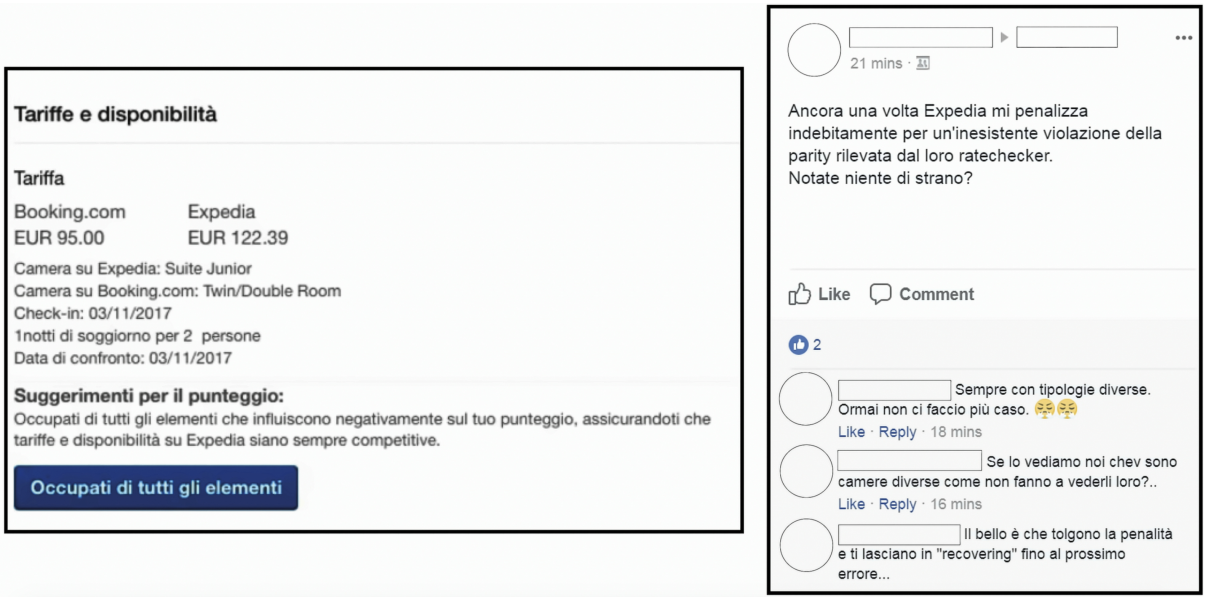


Figure D.3: The Monitoring of PPCs: Evidence from a Facebook Forum of Italian Hoteliers

E Partial Evidence on Loyalty Bookings and Breakfast

In order to explore the mechanisms behind our main findings, it would be good to know whether French or control hotels took actions that, for example, led to explicit offline discounting or the expansion of their loyalty programmes.

Unfortunately, we have no direct evidence regarding these types of actions. As an alternative, in this Appendix, we exploit information on proxies such as loyalty-programme bookings and reservations with breakfast included, although these are *outcomes* rather than *actions* undertaken by hotels. In particular, we test whether the bookings through loyalty programmes and the inclusion of breakfast in the reservation have increased following the Macron Law for hotels in France, compared to the control group. Our implicit assumption is that an increase in these proxies may indicate that hotels have tried to include these as benefits to attract users to the direct channels (online and offline). We acknowledge that this may not be the case and that any eventual increase in the outcome may instead be driven by unobserved factors.

We estimate France–Control differences after the Macron Law using our preferred MC–NN estimator with month fixed effects and hotel–channel fixed effects. Figures E.1 and E.2 show the corresponding event-study plots. Table E.1 reports changes in the percentage of bookings made by loyalty members (Panel A) and the percentage of bookings that included breakfast (Panel B). For reference, the table also reports pre-Macron means by channel in France and in the control group.

Table E.1, Panel A shows a clear rise in loyalty engagement on the WEB channel. The share of WEB bookings made by loyalty members increases by about 5.23% and is statistically significant. Loyalty engagement on OTA does not change, nor does it change on INN. The overall "All Channels" column shows a modest increase. Relative to pre-Macron WEB loyalty shares of about 61.6% in France (68.1% in controls), the WEB effect is economically meaningful, and consistent with hotels leaning on their owned online channel to push loyalty, rather than cutting visible WEB prices.

Table E.1, Panel B tells a similar story for promotions. The WEB share of bookings with breakfast included rises by about 5.04% and is statistically significant. INN, again, does not show a significant change, and OTA shows only a small movement. Given the pre-Macron means, the increase in breakfast bookings on WEB aligns with visible, merchandised perks that are easy to market online, rather than with an expansion offline.

Taken together, and keeping in mind the limitations explained above, these results are consistent with a channel-segmented strategy by hotels. After the Macron Law, hotels may have sought to boost the WEB channel through loyalty programmes and free perks such as breakfast. Because WEB is a visible online channel, they may have adopted this strategy when price differentiation was difficult. Conversely, they did not extend similar perks to INN, where they could instead offer price discounts. In light of the results in the main text, the absence of INN-side perk growth is informative, as it rules out a "perks-driven offline push" and supports a price-based mechanism on the non-visible INN channel.

Table E.1—Estimated Percentage Point Changes in Various Benefits

	OTA (1)	WEB (2)	INN (3)	All (4)
Panel A. Loyalty Members				
	Dependent Variable: Percentage of Loyalty $\times$ 100			
$\tau^{\text{MC-NN}}$	-0.065	5.228***	-0.017	2.269
	(2.341)	(2.017)	(1.744)	(1.546)
Pre-Macron (France)	5.2	61.6	14.9	29.6
Pre-Macron (Control)	10.2	68.1	17.1	36.2
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	4,200	4,212	4,188	23,363
Panel B. Breakfast				
	Dependent Variable: Percentage of Breakfast $\times$ 100			
$\tau^{\text{MCN-NN}}$	3.902*	5.043**	1.812	3.266**
	(2.104)	(2.462)	(1.812)	(1.412)
Pre-Macron (France)	31.0	14.7	58.8	31.7
Pre-Macron (Control)	30.6	16.4	42.5	29.1
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	4,200	4,212	4,188	23,363

Note: This table reports the estimated percentage point changes in the proportion of bookings made by loyalty programme members (Panel A) and proportion of bookings that included breakfast (Panel B). The analyses are performed using the MC-NN estimator. The dependent variable in Panel A is the share of reservations made by loyalty members in a given month and channel, expressed as a percentage and multiplied by 100. The dependent variable in Panel B is the share of breakfast inclusion in bookings for a given month and channel, expressed as a percentage and multiplied by 100. Pre-Macron (FR) and Pre-Macron (CT) denote the pre-treatment mean values of these variables for the respective channels. The WEB, OTA, INN, All column headers indicate the coefficients estimated using subsets of data from the WEB, OTA, INN, and all channels, respectively. Robust standard errors are clustered at the city level and reported in parentheses. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel fixed effects.

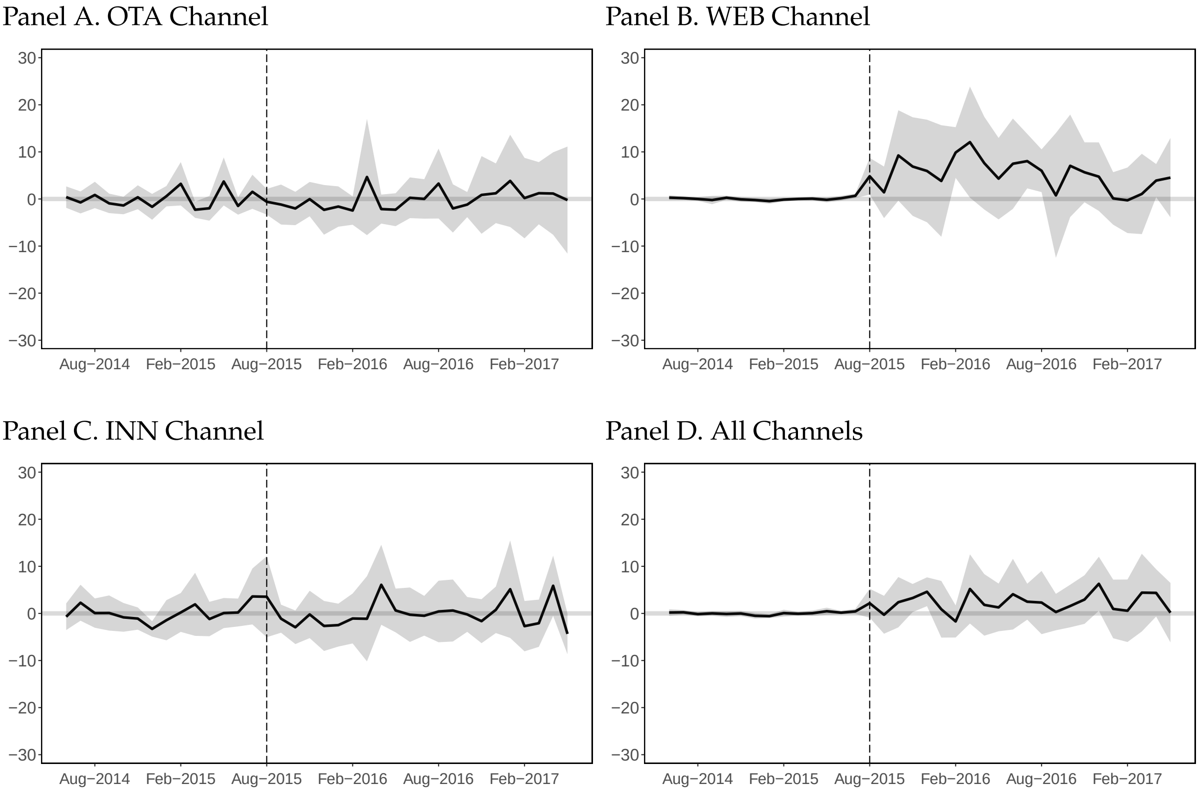


Figure E.1: MC-NN — Percentage Point Changes in Loyalty Bookings

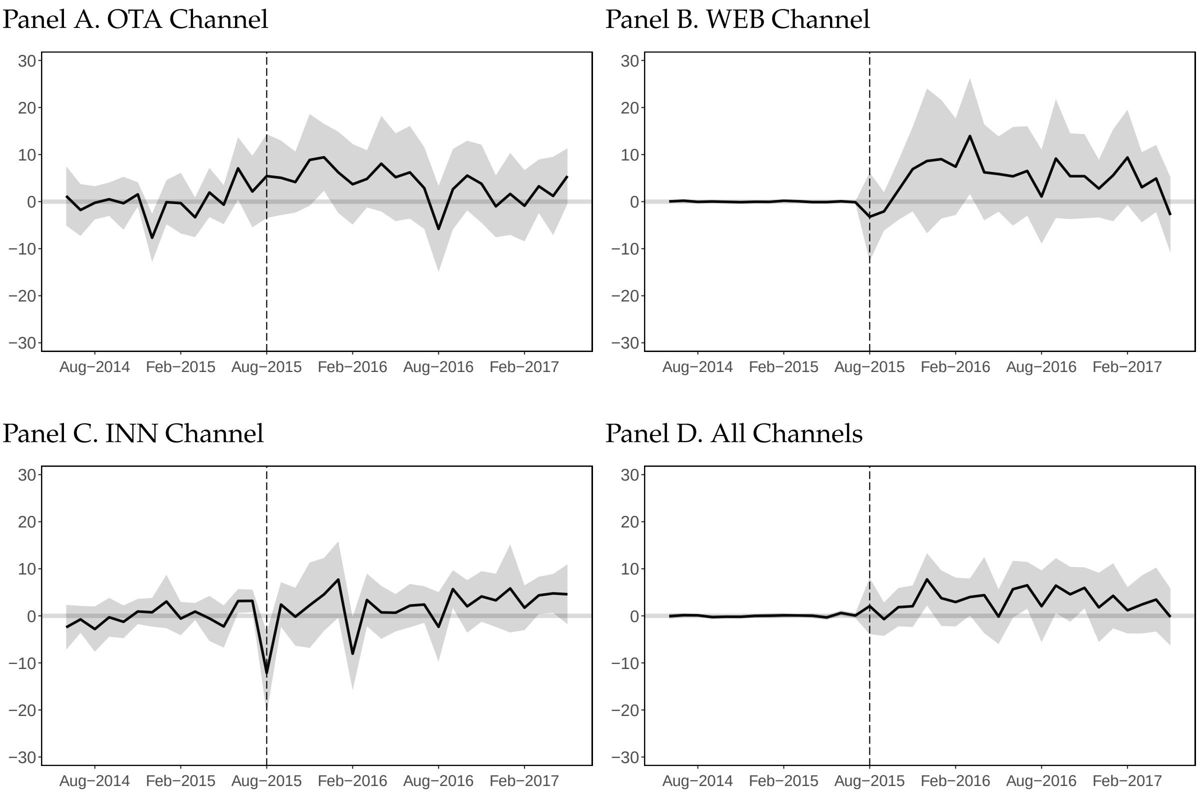


Figure E.2: MC-NN — Percentage Point Changes in Breakfast Inclusion

F Search Trends for the Macron Law and Booking.com's Commitment

The evidence in Figure F.1 indicates that the Macron Law had a notable impact on web searches in France and beyond. By contrast, the commitment by Booking.com to abandon wide PPCs in favour of narrow ones garnered considerably less, almost negligible, attention.[19]

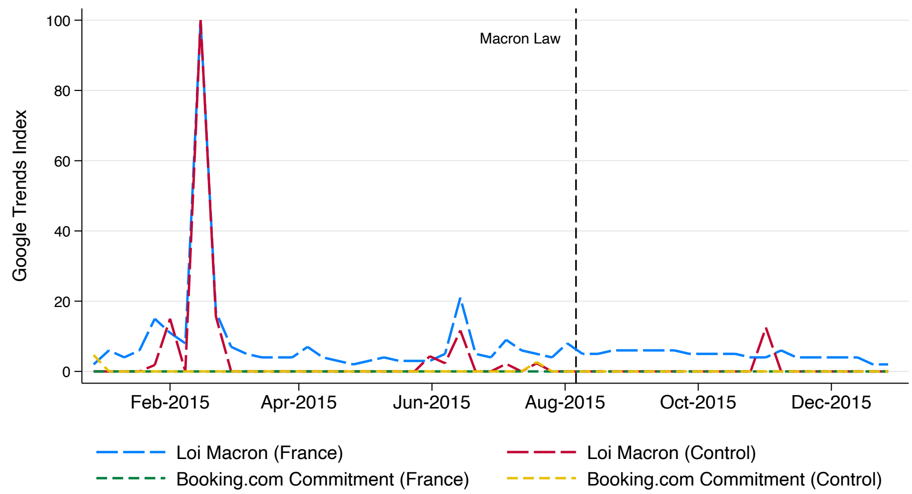


Figure F.1: Google Search Index for "Loi Macron" and "Booking.com Commitment" in France and in the Control Group. Source: Google Trends.

Figure F.2 reinforces this point by focusing on the Google News Search Index. The patterns further confirm users' interest in the Macron Law, while search activity related to Booking.com's commitment remains very limited.

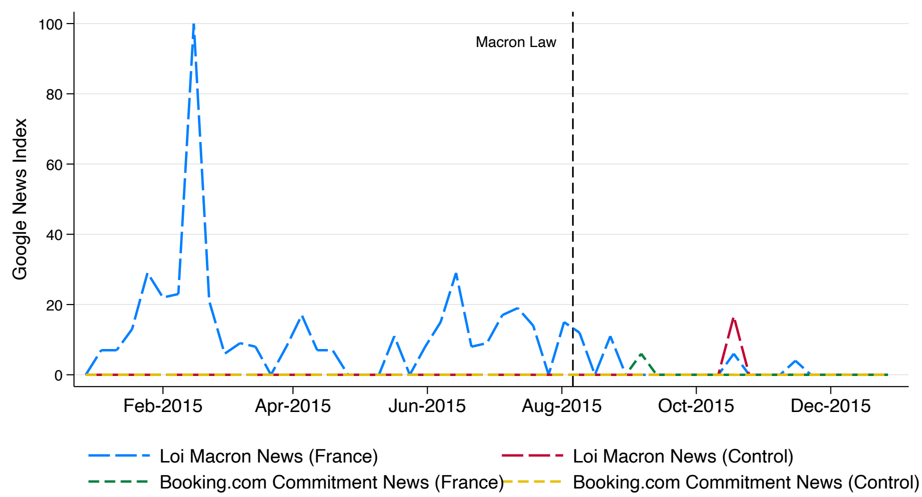


Figure F.2: Google News Search Index for "Loi Macron" and "Booking.com Commitment" in France and in the Control Group. Source: Google Trends.

[19] We tested a number of variations of the search keywords, with no substantial change in the results. We also detected no activity for the search keyword "Expedia commitment".

G Evidence on Room Nights and Occupancy Rates

G.1 Descriptive Evidence on Room Nights and Occupancy Rates

Figure G.1 plots the room night sales and occupancy rates. Panel A shows that the number of room nights sold remained stable over time for the hotels in our estimation sample. Moreover, the difference between French hotels and the control hotels is relatively constant over time. In Panel B, we plot the average monthly occupancy rates of French and control hotels in our estimation sample. The figure shows that occupancy rates are relatively similar across the two groups.

In addition, we leverage monthly data from Insee to examine both the number of room nights and the occupancy rates for the population of hotels in Metropolitan France outside the Parisian region, which allows us to assess whether our estimation sample aligns with broader population trends. The corresponding series are reported in Panel C and Panel D. The overall patterns are very similar for both variables, although hotels in our estimation sample tend to exhibit somewhat higher occupancy rates than the population average.

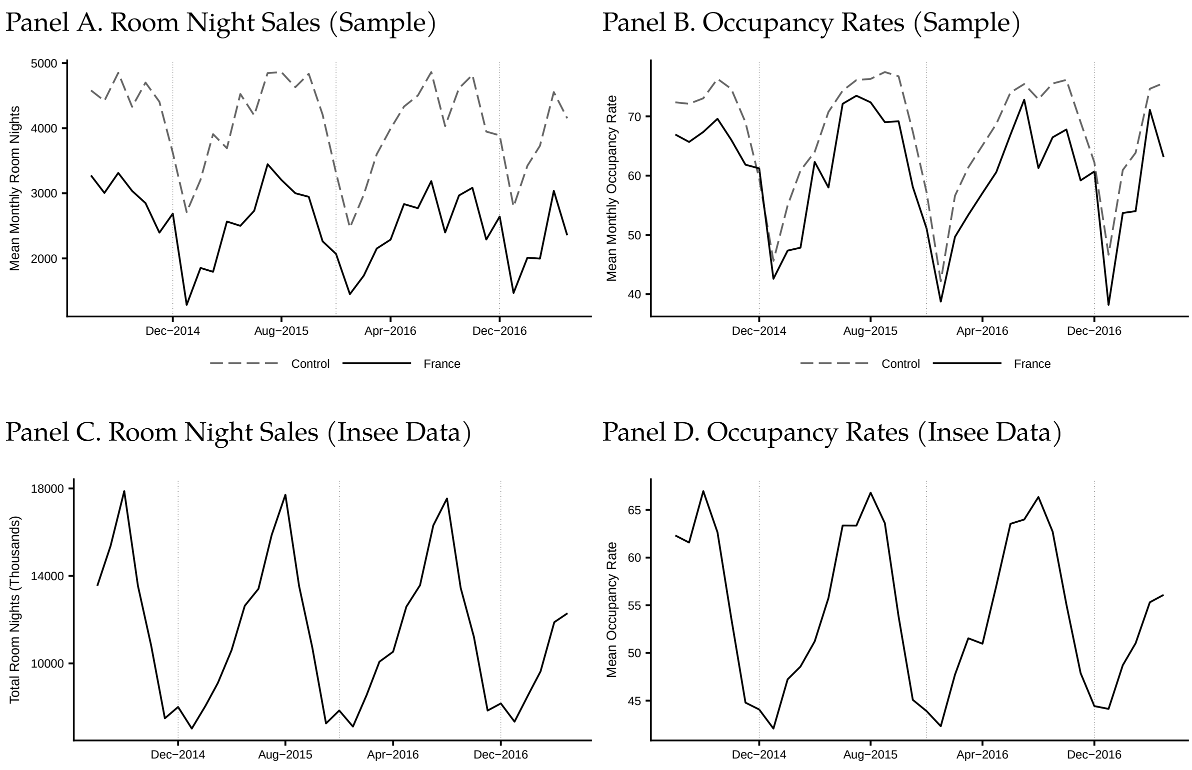


Figure G.1: Average Room Night Sales and Occupancy Rates for Sample and Insee Data

Note: Panels A and B plot the data in our sample, which excludes hotels in Paris. Panels C and D plot the Insee data, which excludes hotels in the Parisian Region.

G.2 Event Studies on Room Nights and Reservations

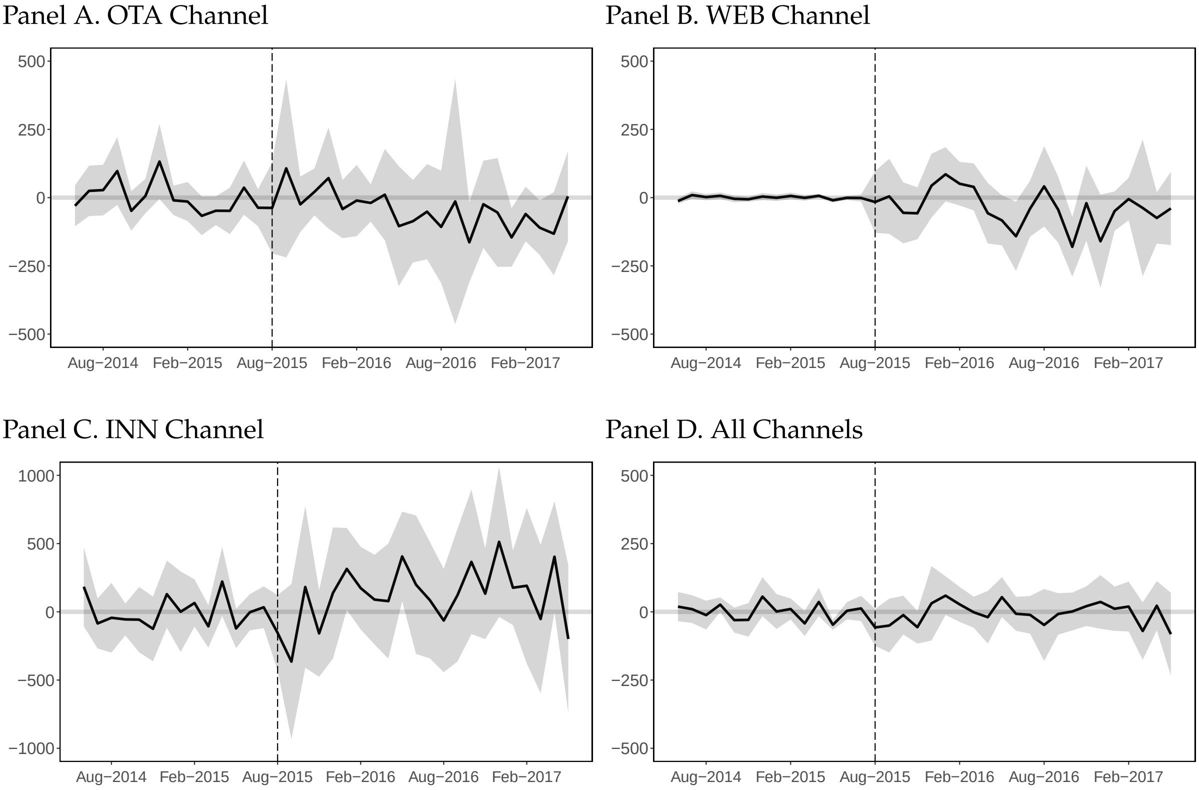


Figure G.2: MC-NN — Effects of the Macron Law on Room Nights

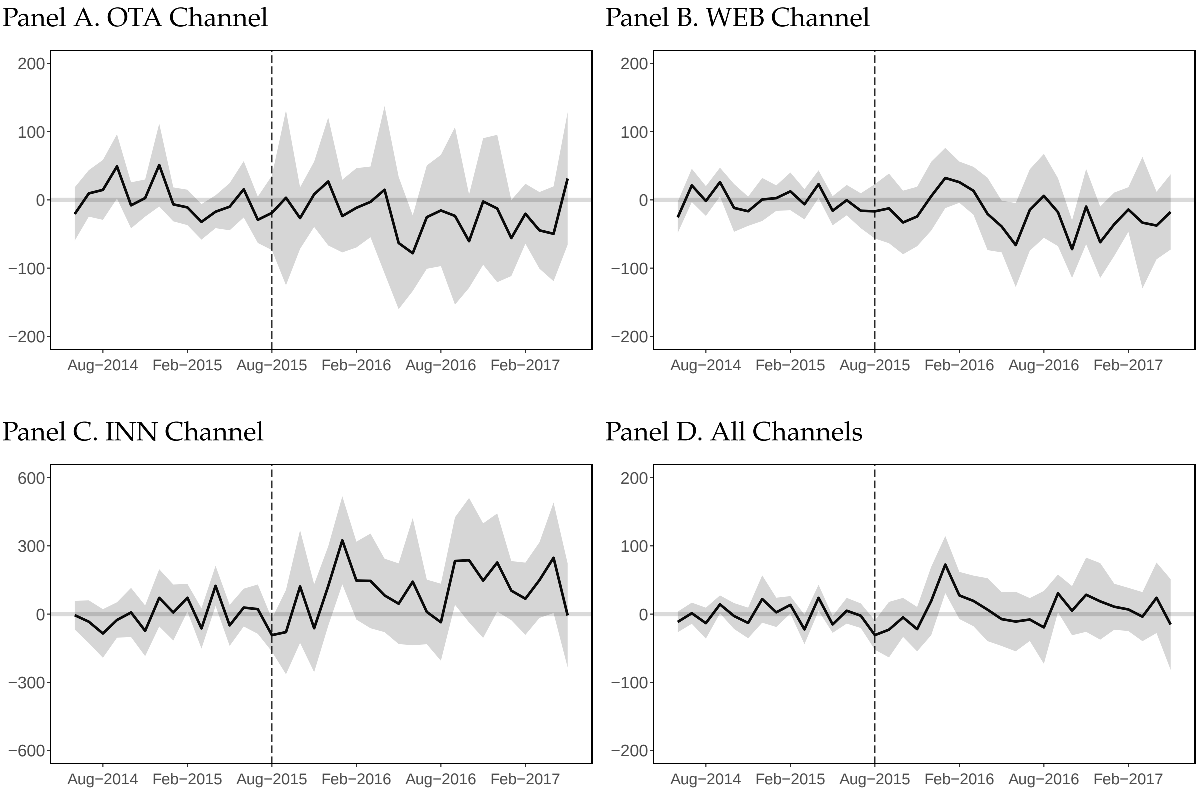


Figure G.3: MC-NN — Effects of the Macron Law on Number of Bookings

H OTA Commission Rates for Hotel Group 2

The descriptive figure in this appendix is generated using data from 5 hotel brands of Group 2. Figure 3 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 normalised OTA commission rates for the two hotel groups, with the rates at the first month in our sample (Relative Month -13) set to 100%.

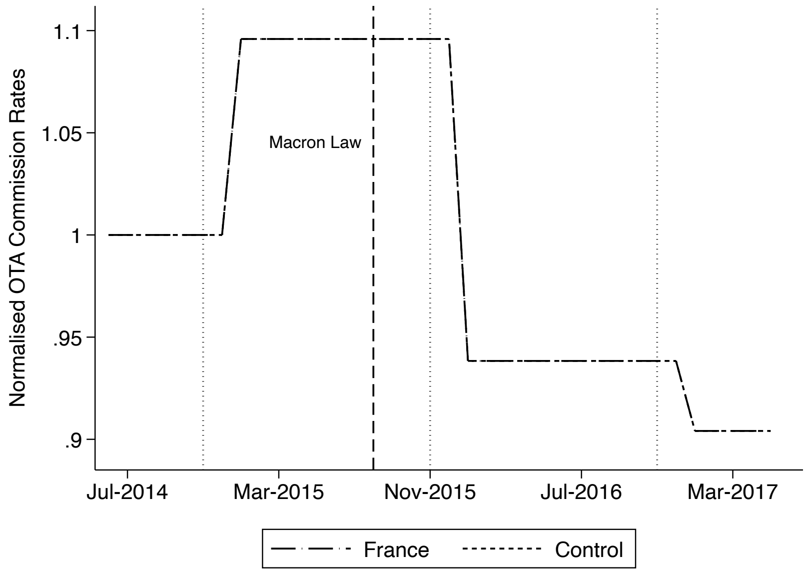


Figure H.1: Normalised OTA Commission Rates: Group 2

Although the data is partial and quite aggregated, the trend reveals a number of insights. First, substantial changes in OTAs' 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 implementation of the Macron Law (dashed line). Indeed, for both groups (Figure H.1 for Group 2 and Figure 3 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 H.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 3 in the text, which indicates that since 2016, the commission rates paid by hotels of Group 1 were lower in France than their sister hotels in the control countries.

I Effects of the Macron Law: Hotel Group 1 Only

Figure I.1 provides the event study graphs referring to the MC-NN estimation in Table 6. Similarly, Figure I.2 plots the event study graphs relating to the MC-NN estimation in Table I.1.

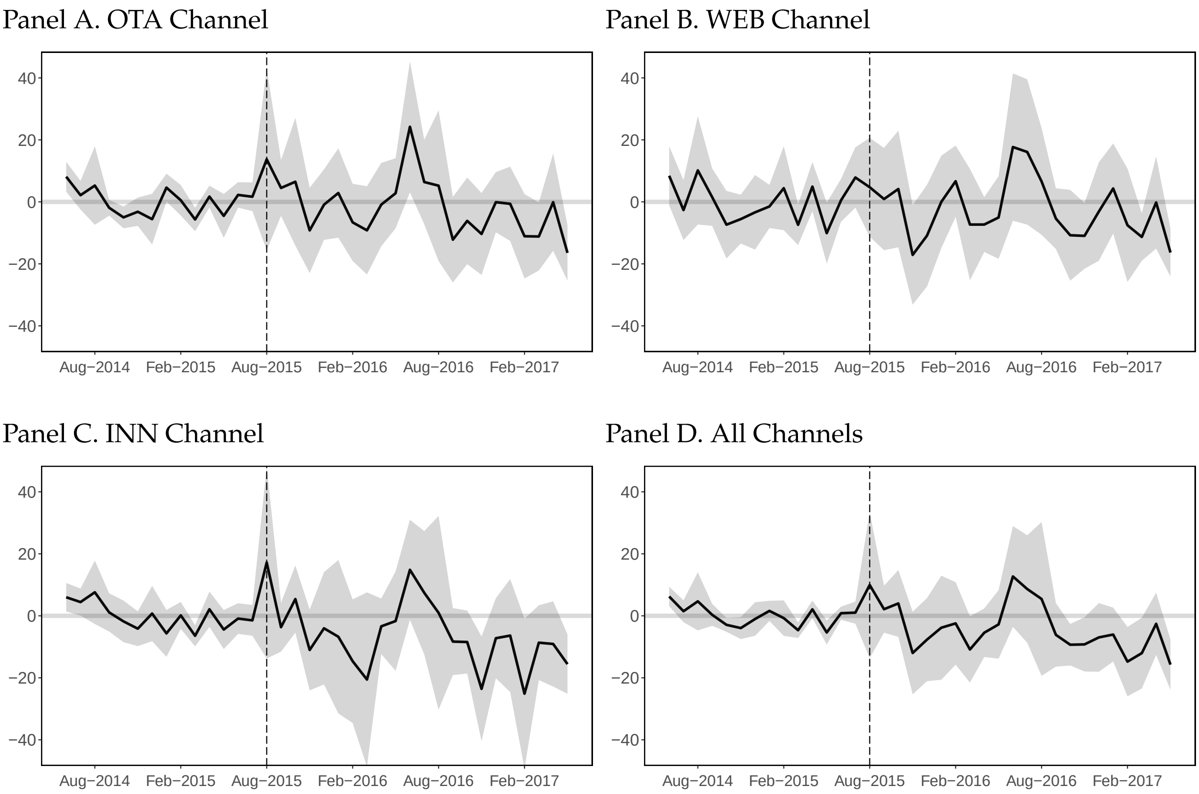


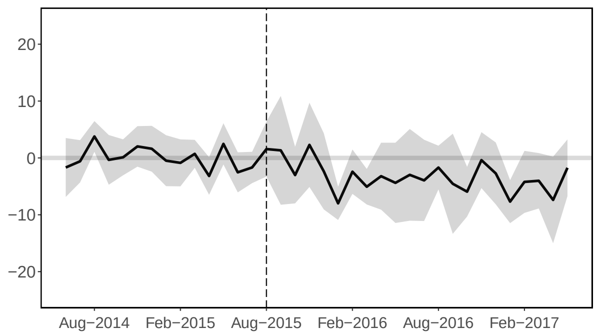
Figure I.1: MC-NN — Price Effects For Hotel Group 1

Table I.1—Effects on Channel Shares: Hotel Group 1

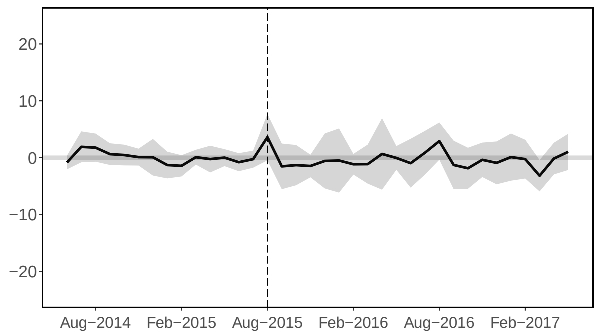
	OTA (1)	WEB (2)	INN (3)
	Dependent Variable: Channel Share × 100		
$\tau^{\text{MC-NN}}$	−3.206***	−0.340	6.289***
	(0.995)	(0.849)	(1.515)
Year-Month FE	✓	✓	✓
Hotel-Channel FE	✓	✓	✓
Observations	2,285	2,296	2,304
No. of Hotels	64	64	64

Note: This table reports the estimated effects of the Macron Law on channel shares of 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. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A. OTA Channel



Panel B. WEB Channel



Panel C. INN Channel

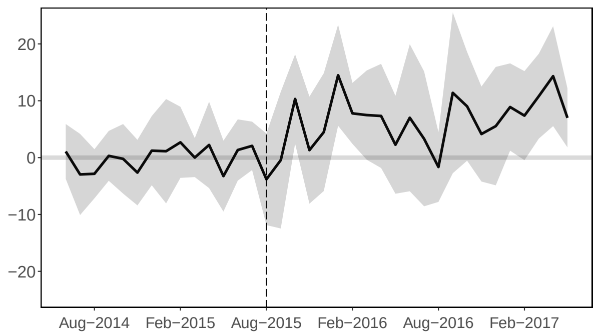


Figure I.2: MC-NN — Effects on Channel Shares For Hotel Group 1

J Main Empirical Analysis Including Paris

The 2015 Paris Terrorist Attack was the most severe terrorist attack (130 deaths, 416 injuries) that occurred in Europe in the 2010s. This tragedy took place on 15 November 2015 in Paris, one of the world-renowned European cities known for its fashion, culinary arts, and culture.

To begin with, we provide graphical evidence based on the room nights variable in our sample. Figure J.1 plots the time series of the monthly room night sales in Paris and in the rest of France. The two series are fairly correlated, reflecting the seasonality of tourism in France. However, following the Paris terror attacks (black dashed line), the figure shows a more pronounced decline for room nights in Paris (red) compared to the rest of France (blue). More precisely, from November to December 2015, the number of room nights sold dropped, on average, by 161 units in the rest of France (from 2350 to 2189, approximately -6.87%) and by 1704 units in Paris (from 4776 to 3071, or approximately -35.69%). Hence, the data suggests that Paris bore the brunt of the immediate tourism downturn following the November 2015 attacks.[20]

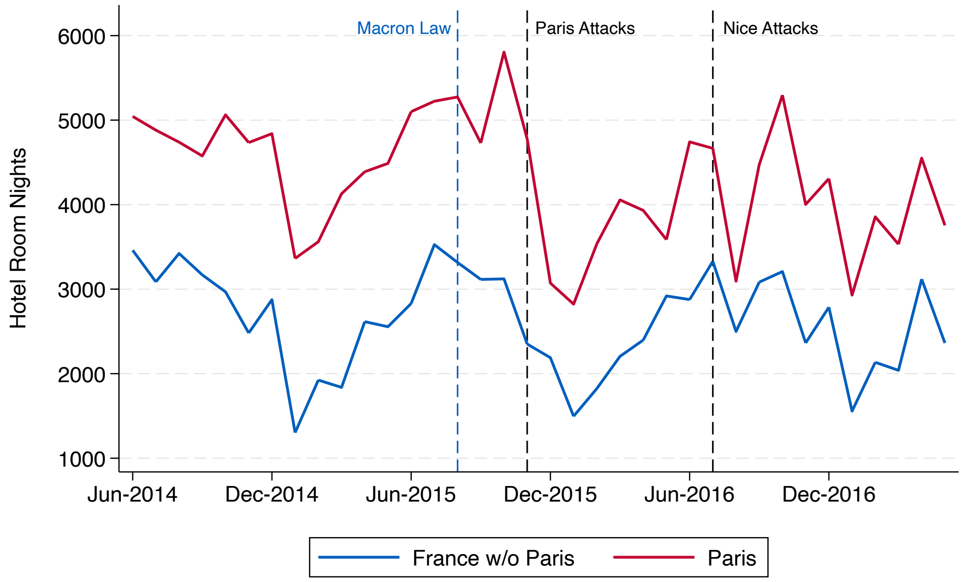


Figure J.1: Hotel room nights in France and terrorist attacks. The graph plots the average monthly room nights for Paris and the rest of France. The blue vertical bar represent the Law Macron, the black bars the Paris (November 2015) and Nice (July 2016) terrorist attacks.

The figure also highlights the impact of the Nice terrorist attack of July 2016. Although this event is somewhat distant from our main shock, it is notable that the major impact of this attack

[20] We note that our data are in line with aggregate room night sales data published by Insee for Paris and Metropolitan France (which includes Paris). According to this data, Paris experienced a decrease of roughly 10% in overnight stays for Quarter 4 of 2015, while Metropolitan France experienced a decrease of only 1% (Insee, 2016).

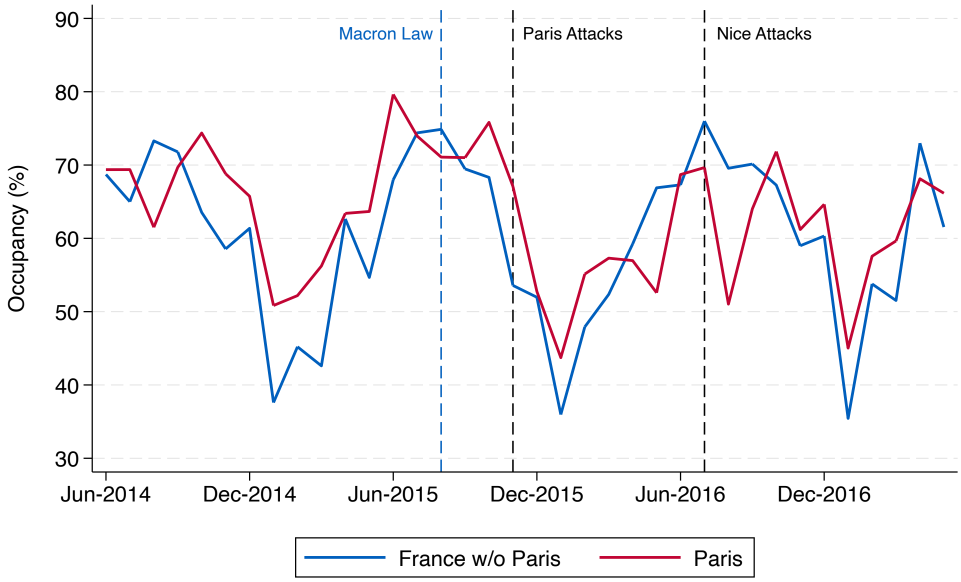


Figure J.2: Hotel occupancy in France and terrorist attacks. The graph plots the average monthly occupancy rate for Paris and the rest of France. The blue vertical bar represent the Law Macron, the black bars the Paris (November 2015) and Nice (July 2016) terrorist attacks.

is on room reservations in Paris, rather than in the rest of the country. Figure J.2 shows very similar patterns when the occupancy rate, rather than room nights, is plotted.

Finally, Table J.1 reports the combined price effects of the Macron Law and the November 2015 Paris Terrorist Attack. The larger magnitude of the coefficients is consistent with the fact that the terrorist attacks had a further negative effect on the prices of the treated hotels. The relative event study graphs are presented in Figure J.3.

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

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
$\tau^{\text{MC-NN}}$	−3.922 (2.699)	−3.484 (2.323)	−5.111*** (1.801)	−4.369** (1.835)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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 coefficients are estimated using the MC-NN estimator. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel fixed effects. Robust and bootstrapped standard errors are clustered at the city level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

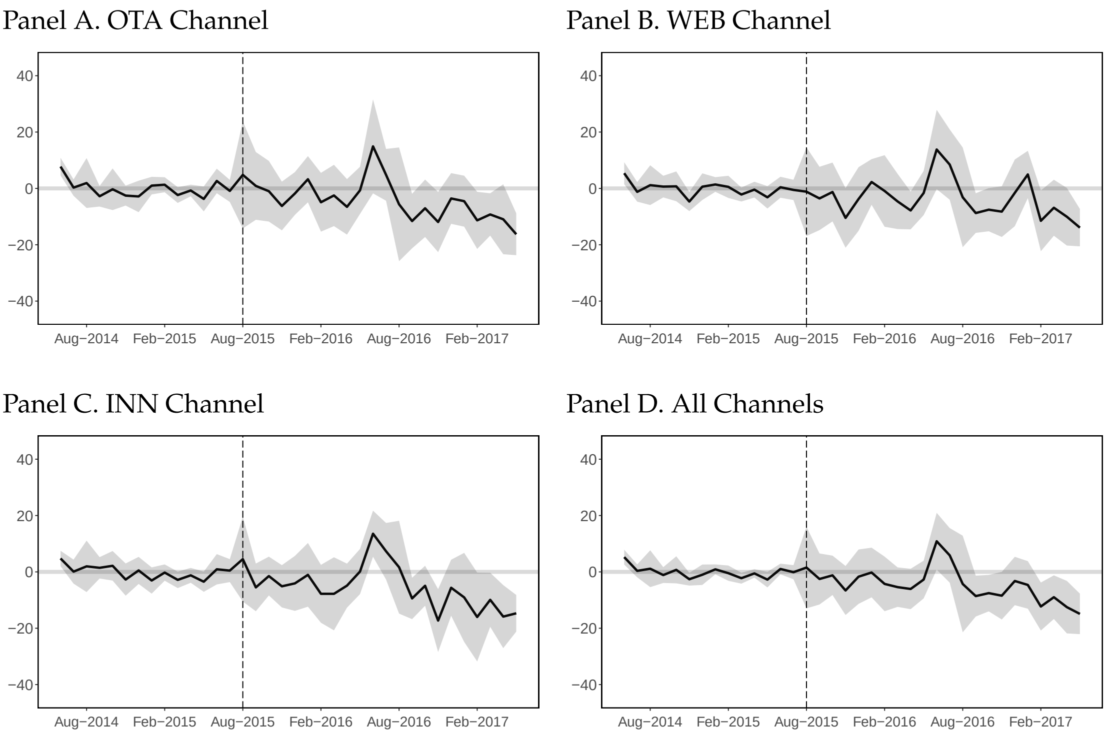


Figure J.3: MC-NN — Price Effects of the Macron Law and Paris 2015 Attack

K Main Empirical Analysis Excluding Paris and Nice

The MC-NN estimation, excluding both Paris and Nice, is in Table K.1. Figure K.1 provides the relative event study graphs.

Table K.1—Price Effects of Prohibiting PPCs (Excluding Paris and Nice)

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
$\tau^{\text{MC-NN}}$	−0.774	−1.517	−5.398**	−2.888
	(2.688)	(2.564)	(2.345)	(2.050)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	5,370	5,382	5,266	28,967

Note: This table reports the price effects of the Macron Law excluding observations from Paris and Nice that were potentially affected by the terrorist attacks. Panel A reports the MC-NN estimates using Equation (5). Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel fixed effects. Robust and bootstrapped standard errors are clustered at the city level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

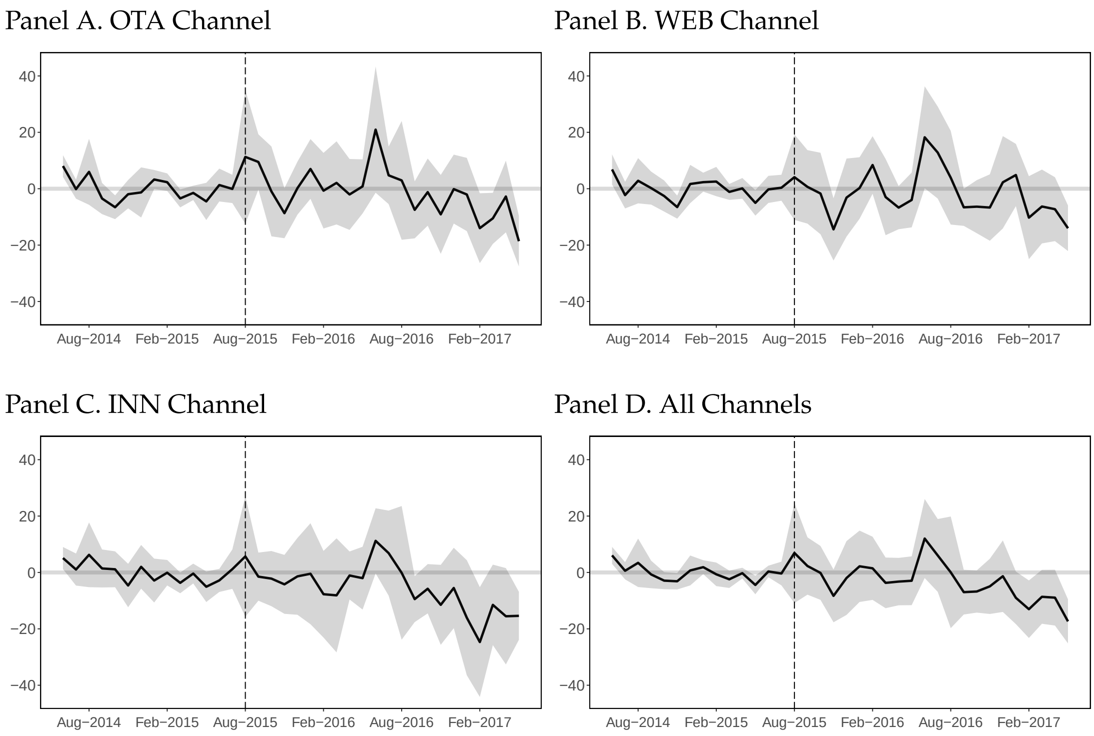


Figure K.1: MC-NN — Price Effects of the Macron Law (Excluding Paris and Nice)

L Anticipation and Lagged Effects

L.1 Anticipation Effects

As with all policies, there is the possibility for the Macron Law to be anticipated. The weeks between the announcement and commencement of the policy may provide some time for platforms and hotel chains to re-adjust their strategies. However, we believe that the 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 not be able to lower the prices on their official websites beforehand, as it would be a breach of the PPCs.

Our robustness checks confirm these speculations. As shown in Table L.1, the price effects of shifting the treatment timing by one and two months before the Macron Law are quantitatively similar to those reported in the main results table (Table 3), which suggest that it is unlikely that the legislation was not anticipated in practice. Figures L.1 and L.2 provide the relative event study graphs.

Table L.1—Estimated Price Effects of the Macron Law: Anticipation

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. Anticipation: 1 Month				
$\tau^{\text{MC-NN}}$	−0.923	−1.361	−4.483**	−2.798
	(2.603)	(2.134)	(2.089)	(1.959)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	5,406	5,418	5,302	29,175
Panel B. Anticipation: 2 Months				
$\tau^{\text{MC-NN}}$	−0.605	−1.383	−4.581**	−2.637
	(2.392)	(2.205)	(2.186)	(1.916)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	5,406	5,418	5,302	29,175

Note: This table reports the estimated anticipation effects of the Macron Law on prices. The analyses are performed using the MC-NN estimator following Equation (5). Panel A reports the estimated coefficients by for one month of anticipation, and Panel B reports that for two months. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

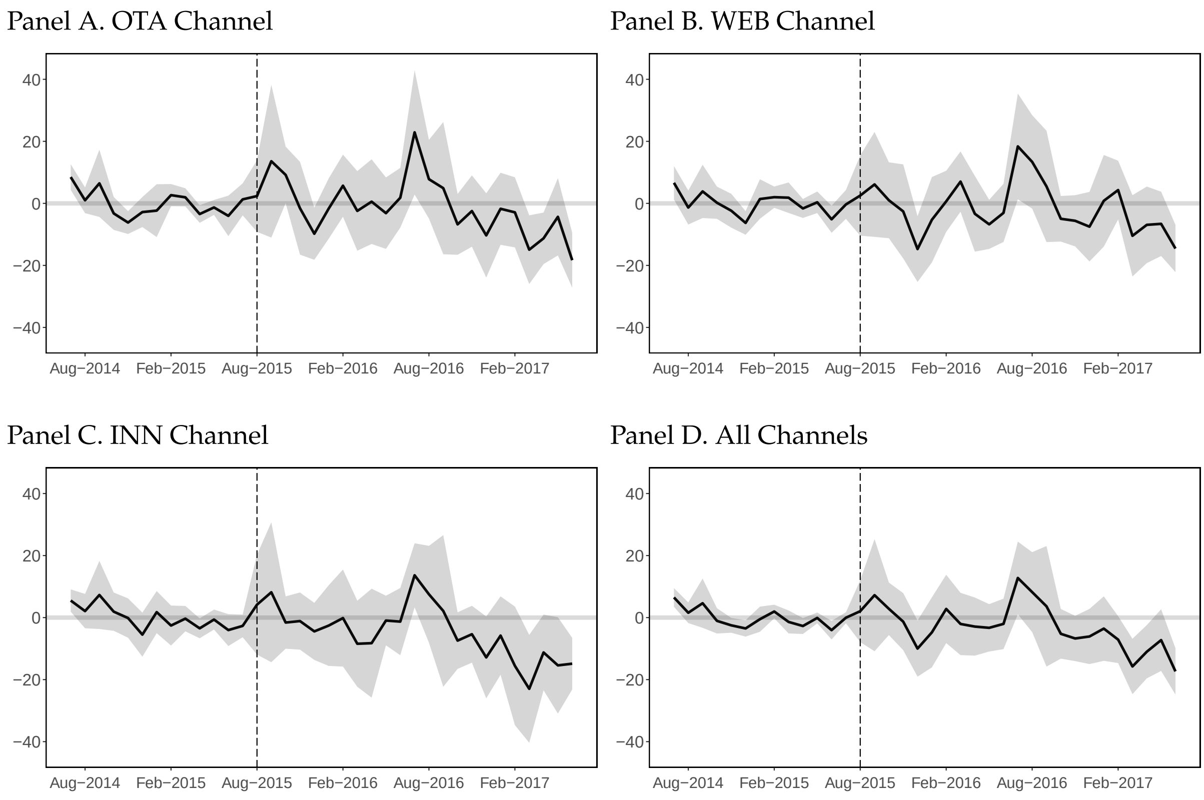


Figure L.1: MC-NN — Anticipation Effects on Prices (1 Month)

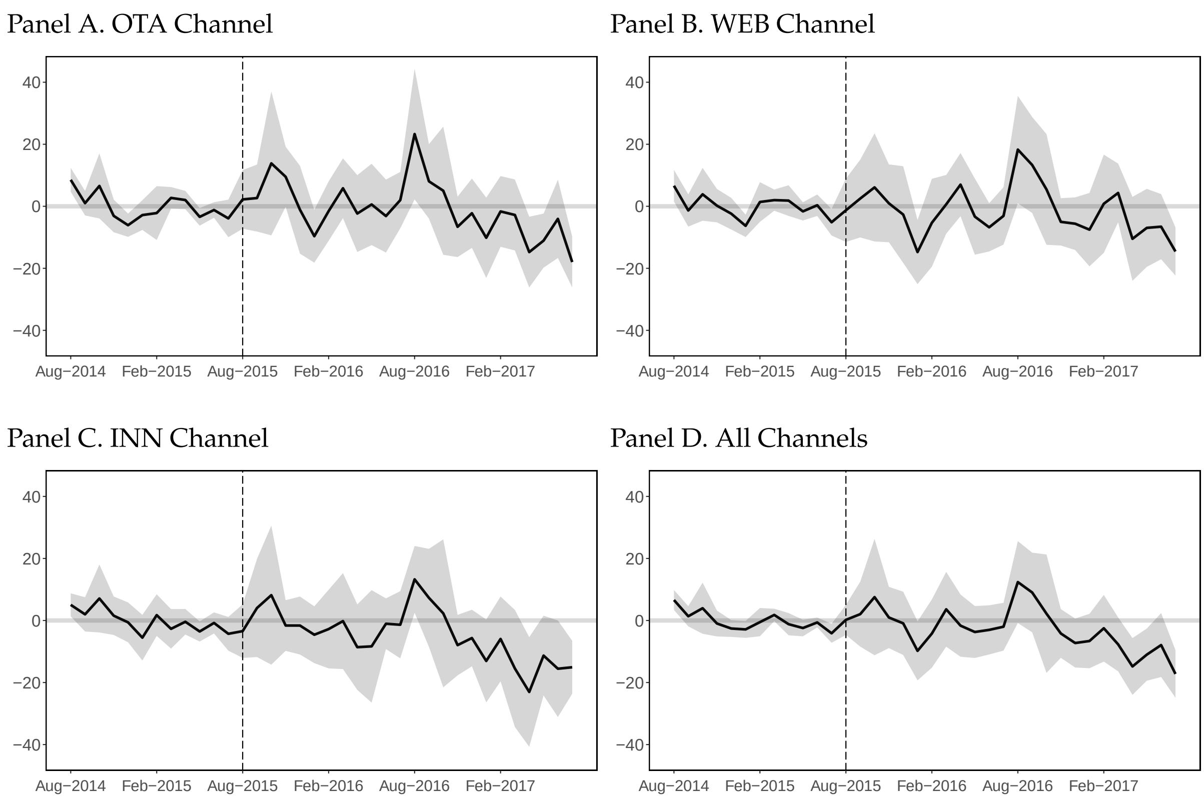


Figure L.2: MC-NN — Anticipation Effects on Prices (2 Months)

L.2 Lagged Effects

We also consider the possibility that the treatment effects were *lagged*. In other words, the rooms booked after the Macron Law may undergo weeks before they are checked in. In addition, prices may take some 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 L.2, we find qualitatively similar but more pronounced effects than our main results, suggesting that the effects of the legislation may have been lagged. Figures L.3 and L.4 provide the relative event study graphs.

Table L.2—Estimated Price Effects of the Macron Law: Lagged Effects

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. Lagged Effects: 1 Month				
$\tau^{\text{MC-NN}}$	−3.200	−2.631	−6.622**	−4.360*
	(2.772)	(2.934)	(3.026)	(2.503)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	5,406	5,418	5,302	29,175
Panel B. Lagged Effects: 2 Months				
$\tau^{\text{MC-NN}}$	−4.083	−2.755	−6.737**	−4.725**
	(2.866)	(2.826)	(3.178)	(2.388)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	5,406	5,418	5,302	29,175

Note: This table reports the estimated lagged effects of the Macron Law on prices. The analyses are performed using the MC-NN estimator following Equation (5). Panel A reports the estimated coefficients by for one month of lag, and Panel B reports that for two months. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

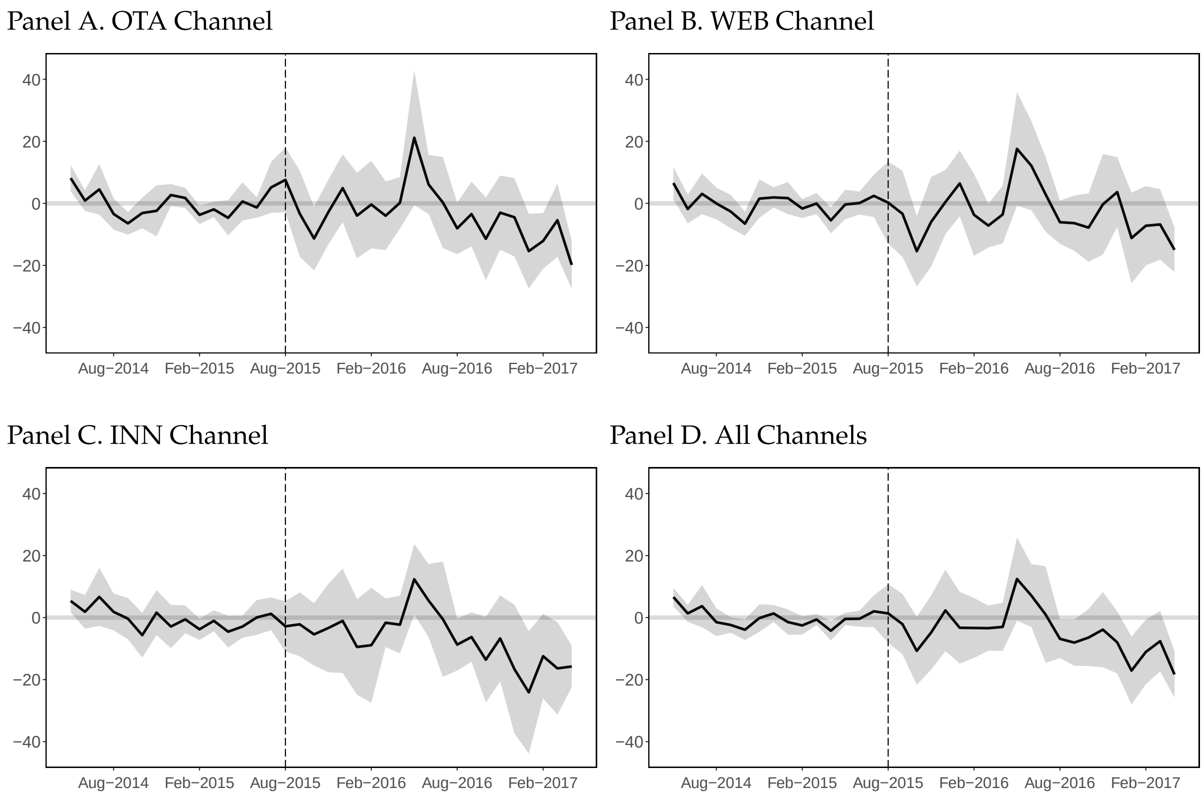


Figure L.3: MC-NN — Lagged Effects on Prices (1 Month)

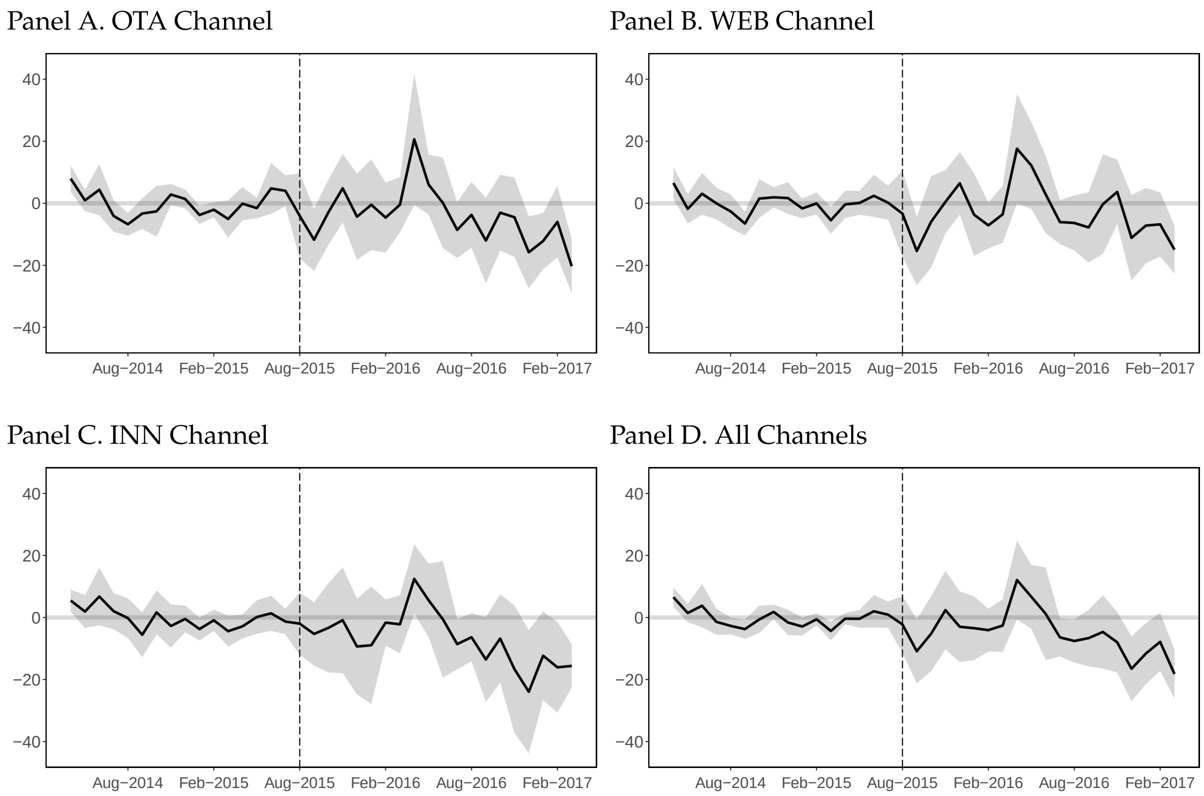


Figure L.4: MC-NN — Lagged Effects on Prices (2 Months)

M Prices in France and in the Control Group

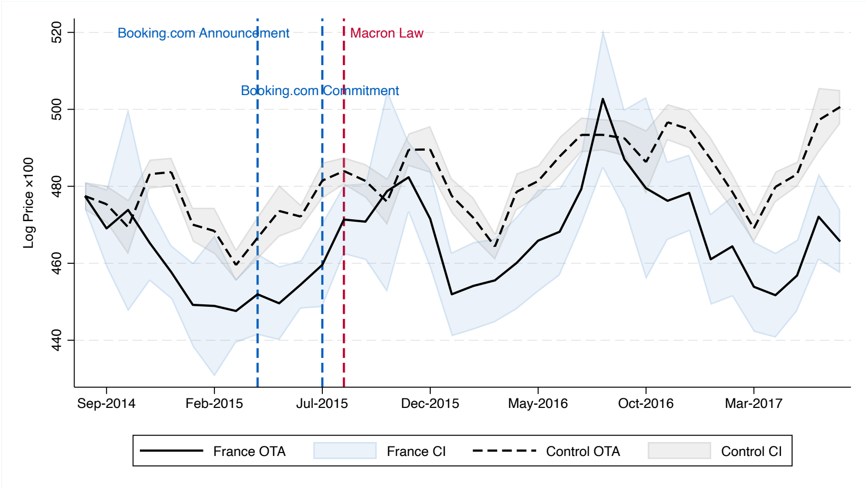
In Figure M.1, we plot the average monthly prices for hotels in France and in the control groups across our main channels: WEB (Panel A), OTA (Panel B) and INN (Panel C). The panels show no clear price decrease for either group following the major OTAs' commitment in April 2015, nor after the start of its implementation in July 2015. As these events were applied EU-wide, they could have affected both the French and the control hotels. Yet, in both groups, the price trends appear to be following their previous seasonal patterns.

In particular, we notice that OTA and WEB display common seasonal patterns throughout the sample period. For the INN channel, we do not observe a systematic decrease in prices among the control hotels, nor even a flattening of the trend. In fact, INN prices appear to rise in control countries, while French INN prices decline relative to the controls. As discussed in the main text, this divergence is likely tied to a reduction in commission rates for French hotels.

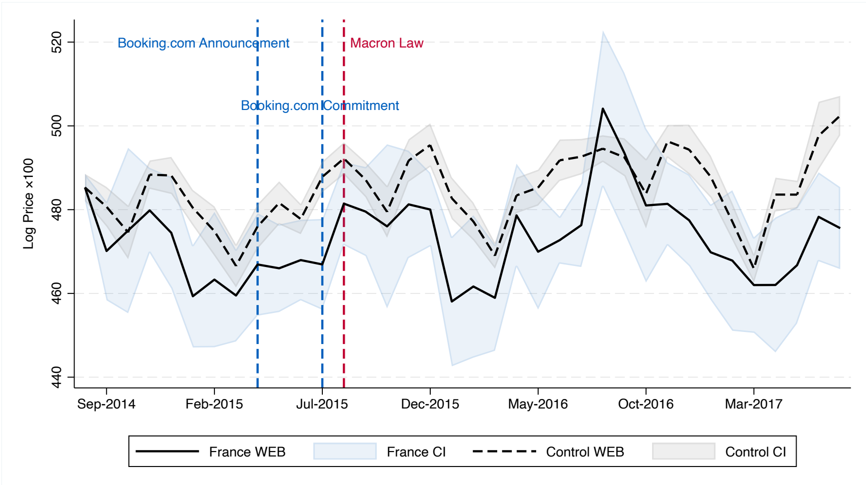
In summary, the data suggest that the switch from wide to narrow PPCs, and the subsequent opportunity to lower prices on INN channels starting in July 2015, did not significantly alter the pricing behaviour of hotels in our sample *prior* to the main policy intervention that we study: the Macron Law.

Moreover, the observed common patterns between the prices of the treated and the control group provide supporting evidence for the hypothesis of no spillover effects of the French policy change on hotel pricing in other countries *after* the implementation of the Macron Law. While we cannot entirely rule out the possibility of spillover effects across EU countries, the evidence suggests that the pre-shock patterns have been mostly unaffected, and a sharp drop in the prices for both the treated and the control group has not taken place after the implementation of the policy. This mitigates concerns about the possibility of strong spillovers of the French intervention onto hotels in the control group.

Panel A. OTA Prices



Panel B. WEB Prices



Panel C. INN Prices

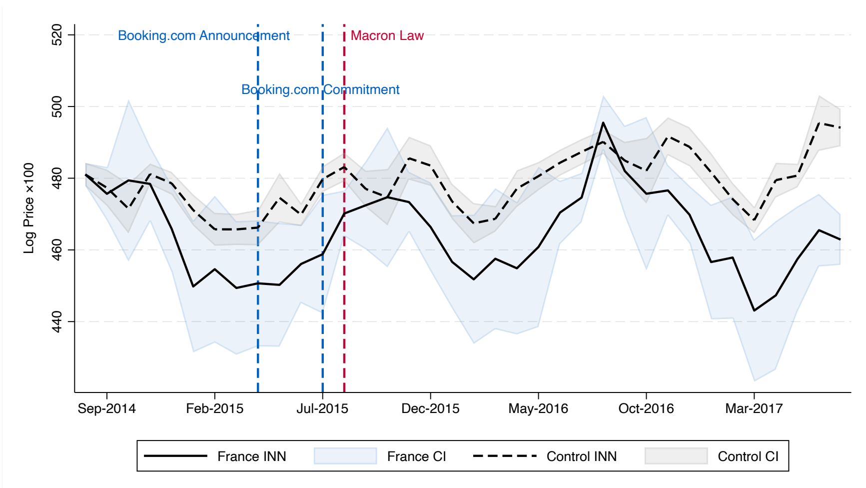


Figure M.1: Price dynamics of each sales channel. Plotted variable: logarithm of room price, multiplied by 100. The vertical lines represent: before and after Booking.com's commitment (July 2015) and its announcement (April 2015) in blue, the Macron Law (August 2015) in red.

N Additional Robustness Checks

N.1 Triple-Difference: Price Effects Across Channels

The baseline analyses examined the effects of the Macron Law on each sales channel separately. This approach may overlook the evolution of price differences between the channels. Indeed, hotels may vary in how they price across channels, and costs (like OTAs' commissions) do not always align with price rankings. In order to attenuate these concerns, we adopt a triple-difference specification that pools all channels together. The results are presented in Table N.1. Comparing Panel A of Table N.1 with the baseline results in Table 3 confirms the robustness of our approach. In Table N.1, the baseline category (channel) is OTA. This choice is justified by the fact that OTAs were directly targeted by the regulations. Hence, all results are to be interpreted as the difference between the OTA channel and the other channels (INN and WEB). This holds with the exception of Column (2), which compares INN to WEB.

The coefficients in the first line of Columns (1), (3) and (4) show that the impact of the Macron Law on OTA prices in France with respect to the control group is robust, as they are in line with the estimated effect in Column (1), Panel A of Table 3. Column (2) also indicates that the estimated effect for WEB is in line with that presented in Column (2), Panel A of Table 3. We also note that the statistical significance of the effects is confirmed. Similar considerations also apply to the interaction terms, which capture the differences between channels. For example, relatively to the control group, the prices on INN decreased significantly more in France compared to those on OTA (Column 1) and on WEB (Column 2). According to Column (3), instead, the prices on WEB in France decreased slightly more than those on OTA, but not significantly so. Qualitatively identical results and similar magnitudes are also observed when all three channels are included in the same specification (Column 4).

Panel B focuses on a triple-difference specification based on the MC-NN estimation method. Due to the lower flexibility of the estimation method, we estimated a specification based on the price *differences* across the three main sales channels. The reported estimated price effects are fully in line with those reported in Panel A, as well as in Table 3 in the main text. Finally, Figure N.1 presents the event study plots using to the MC-NN estimates. The dynamic treatment effects of this specification largely reflect the average effects discussed above: whereas the difference between WEB and OTA (Panel A) fluctuates around zero both before and after the policy change, a negative effect can be seen in the difference between INN and OTA, as well as between INN and WEB (Panels B and C) following the implementation of the Macron Law.

Table N.1—Price Effects Across Channels: Triple Differences

	INN-OTA (1)	INN-WEB (2)	WEB-OTA (3)	INN-WEB-OTA (4)
	Dependent Variable: Log Price × 100			
Panel A. TWFE-DID				
Post France	−1.652	−1.980	−1.687	−1.666
	(2.508)	(2.377)	(2.510)	(2.507)
Post France INN	−4.015**	−3.694*		−4.009**
	(1.752)	(1.872)		(1.751)
Post France WEB			−0.308	−0.316
			(2.290)	(2.289)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	10,708	10,720	10,824	16,126
No. of Hotels	156	156	156	156
	INN-OTA (1)	INN-WEB (2)	WEB-OTA (3)	
	Dependent Variable: Log Price × 100			
Panel B. MC-NN				
$\tau^{\text{MC-NN}}$	−3.901**	−3.427	−0.241	
	(1.911)	(2.114)	(2.625)	
Year-Month FE	✓	✓	✓	
Hotel-Channel FE	✓	✓	✓	
Observations	5,272	5,272	5,272	
No. of Hotels	156	156	156	

Note: Panel A reports the TWFE estimates using a *triple-difference* version of Equation (3), including channel interaction terms. Panel B reports the estimated price effect *differences* of the Macron Law across the three main sales channels, using the MC-NN estimator. Year-Month FE and Hotel-Channel FE are included. Robust standard errors are clustered at the city level and reported in parentheses. The non-parametric bootstrap procedure is performed 1,000 times. $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$.

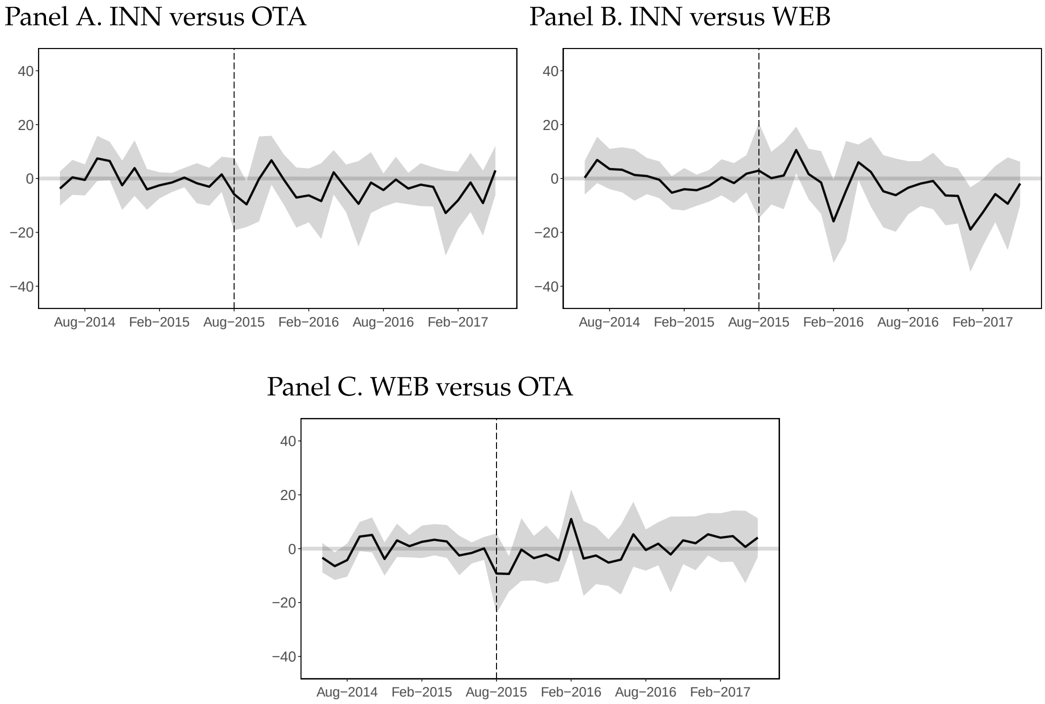


Figure N.1: Price Effects Across Channels: Triple Differences

N.2 Nearest Neighbour Matching Estimator

In this appendix, we follow the methodology in Deryugina et al. (2020), which combines seasonal adjustments, nearest-neighbour matching based on Abadie and Imbens (2006) and Abadie and Imbens (2011), and DID. The procedure to construct a counterfactual for our treated hotels consists of two steps. First, we apply a seasonal adjustment to our data. We use the pre-treatment periods (14 months) to compute the mean price (in logarithms) and standard deviation for each hotel-channel unit, and then calculate a standardised variable, z_{it}. Second, we perform a matching procedure. For each hotel-channel unit, we compute the distance between the treated units and all the control units in terms of the standardised variable, z_{it}, in the pre-treatment period. We select the five control units with the lowest total distance from each of the treated units throughout the pre-treatment period to construct the counterfactuals. On that basis, we run a TWFE regression on the sample selected through matching.

Table N.2 provides the estimates, which prove fairly robust and in line with Table 3. We see that the magnitude and statistical significance of the NN5 coefficients are broadly comparable. In particular, the use of seasonal adjustment and matching seems to indicate, even more clearly, a small and non-significant price effect of the removal of PPCs on OTA and WEB, the two main visible channels. As in our baseline, the only significant effect is observed on INN, although the magnitude is slightly smaller than in the MC-NN estimates. We note that the standard errors are broadly similar between the estimators, and we therefore treat NN5 as a complementary robustness check alongside MC-NN.

Table N.2—Price Effects of Prohibiting PPCs: Nearest Neighbour Matching

	OTA (1)	WEB (2)	INN (3)
	Dependent Variable: Log Price × 100		
τ^{NN5}	−1.888	−1.730	−3.732*
	(2.563)	(2.455)	(2.045)
RMSE	17.731	16.447	19.500
Year-Month FE	✓	✓	✓
Hotel-Channel FE	✓	✓	✓
Observations	1,797	1,906	1,906
No. of Hotels	50	53	53

Note: This table reports reports the estimates of Equation (3) when the control group is selected through the five nearest neighbours procedure in Deryugina et al. (2020). Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel fixed effects. Robust standard errors are clustered at the city level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

O Heterogeneity Analysis

O.1 Descriptive Information on Hotel Heterogeneity

Table O.1 presents the characteristics of hotels based on their pre-treatment statuses. The cutoff threshold of each panel was carefully chosen after considering the population statistics and ensuring that the DID exercise had a relatively balanced number of treated hotels for the Low and High categories. As we can see, there exists a clear pattern in the characteristics of hotels. Hotels that *ex ante* relied less on OTA as their sales channel have higher star ratings, more rooms, higher occupancy rates, and are more expensive. Similarly, hotels with *ex ante* higher occupancy rates are also more high-end, have more rooms, and are more expensive.

Table O.1—Summary of Hotel Characteristics By Pre-Treatment Status

	Star Ratings	Hotel Capacity	Review Score	Occupancy Rate	Average Price	Room Nights
Panel A. OTA Shares (20% as cutoff)						
Low	4.0	211.1	8.3	0.69	143	4362
(n = 17674, N = 90)	(0.6)	(119.9)	(0.4)	(0.17)	(51.4)	(1065)
High	3.8	164.1	8.4	0.62	139	3206
(n = 11501, N = 67)	(0.7)	(138.8)	(0.4)	(0.14)	(41.9)	(751)
Panel B. Occupancy Rate (65% as cutoff)						
Low	3.9	157.1	8.4	0.56	135	2585
(n = 12244, N = 69)	(0.6)	(77.5)	(0.4)	(0.17)	(54.7)	(717)
High	4.0	217.4	8.4	0.75	146	4876
(n = 16931, N = 88)	(0.7)	(154.5)	(0.4)	(0.15)	(41.2)	(1089)

Note: This table reports the mean characteristics of hotels by their pre-treatment status. Standard deviations are reported in parentheses. Panel A divides the sample into low and high OTA reliance, while Panel B divides the sample into low and high occupancy rates. The observations are denoted using lowercase n, while the number of hotels is indicated using uppercase N. "Star Ratings" reports each hotel's average number of star ratings. "Hotel Capacity" denotes the average number of rooms per hotel. "Review Score" reports each hotel's static average review score displayed on OTAs."Occupancy Rate" denotes the average occupancy rate. The "Average Price" column reports the average price per room sold in each hotel. "Room Nights" indicates the average monthly room-night sales of each hotel.

O.2 Heterogeneous Price Effects: Pre-Treatment OTA Reliance

Table O.2, Panel A reports the estimated price effects of the Macron Law for French 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. We note that the magnitude of 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 direct offline channel, INN, where we document a statistically significant price decrease of -6.913% in Panel A, but a non-significant coefficient of -2.860% in Panel B. The decrease in INN for Table O.2, Panel A is also significantly larger than the one in the baseline in Table 3, Panel B.

Generally, Panel B shows that the hotels that were *ex ante* more reliant on OTAs decreased their prices across the three main booking channels less than their less reliant counterparts (Panel A), and none of their decreases is statistically significant. The relative event study graphs are in Figure O.1 and O.2.

Table O.2—Heterogeneous Price 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%				
$\tau^{\text{MC-NN}}$	−1.701	−1.874	−6.913**	−3.698
	(3.488)	(2.952)	(2.762)	(2.448)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	5,276	5,288	5,172	28,486
No. of Hotels	156	156	155	156
Panel B. OTA Share Greater Than 20%				
$\tau^{\text{MC-NN}}$	−0.883	−1.632	−2.860*	−2.494
	(2.448)	(2.598)	(1.710)	(1.819)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

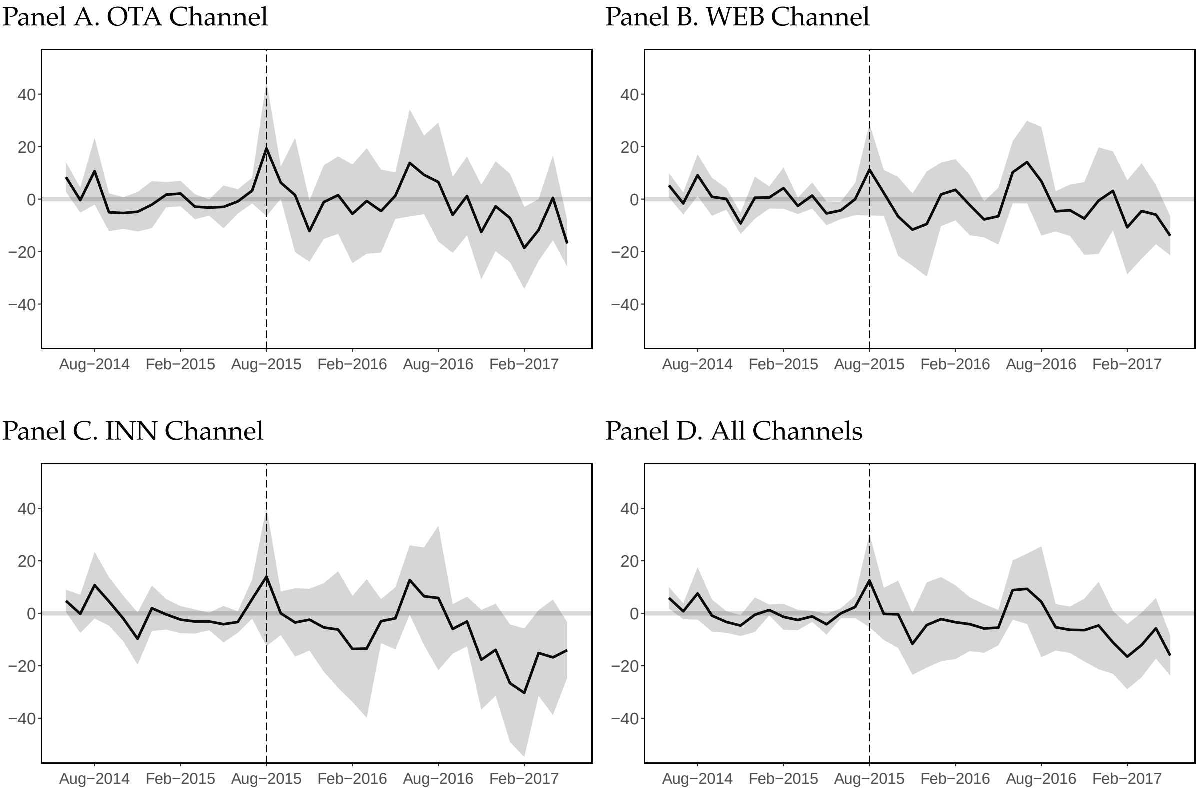


Figure O.1: MC-NN Analysis of Prices — OTA Reliance Less Than 20%

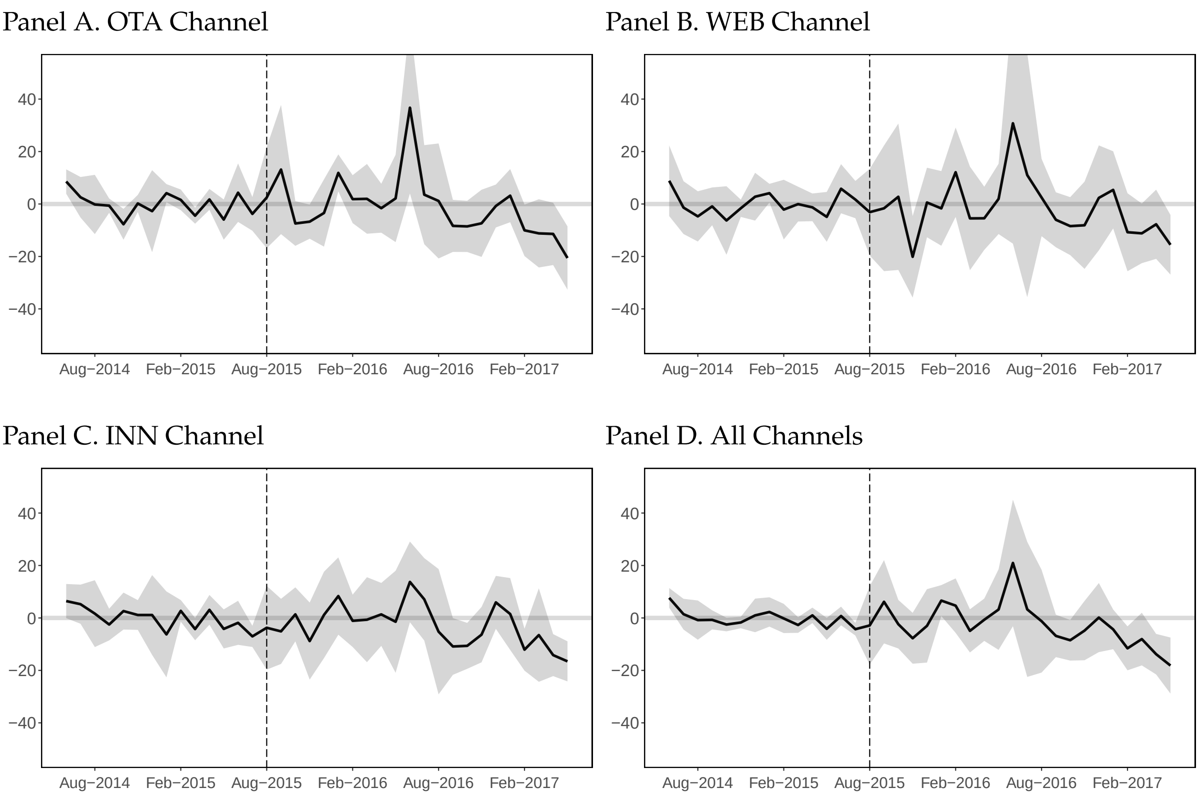


Figure O.2: MC-NN Analysis of Prices — OTA Reliance More Than 20%

O.3 Heterogeneous Price Effects: Pre-Treatment Occupancy Rate

For this analysis, we split the hotels into two categories according to their *pre-treatment* occupancy: those with an average pre-treatment occupancy rate of less than 65%, the approximate mean for the hotels in our sample, and those with a pre-treatment occupancy rate greater than or equal to that threshold. To address the issue of reduced power and account for potential cross-country heterogeneity in occupancy levels, we allow control units from the entire sample to be used in the matrix completion procedure. The estimated coefficients are in Table O.3. The event study plots are in Figures O.3 and O.4.

Table O.3—Heterogeneous Price Effects: Pre-Treatment Occupancy Rates

	OTA (1)	WEB (2)	INN (3)	All (4)
	Dependent Variable: Log Price × 100			
Panel A. Occupancy Less Than 65%				
$\tau^{\text{MC-NN}}$	−0.302	−1.184	−4.606*	−2.533
	(3.014)	(2.945)	(2.414)	(2.174)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel FE	✓	✓	✓	✓
Observations	5,320	5,332	5,216	28,698
No. of Hotels	156	156	155	156
Panel B. Occupancy More Than 65%				
$\tau^{\text{MC-NN}}$	−4.959**	−3.749**	−7.779***	−5.363***
	(2.343)	(1.542)	(3.221)	(1.749)
Year-Month FE	✓	✓	✓	✓
Hotel-Channel 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. Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel FE (δ_i) denotes the hotel-channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Our findings suggest that the French hotels with lower *ex ante* occupancy (Panel A), even without a formal contractual obligation to maintain price parities, were hesitant to decrease their prices on visible online channels. This may be due to concerns that their occupancy rates would be further affected. On the other hand, the French hotels with higher *ex ante* occupancy (Panel B) leveraged the prohibition of all types of PPCs and reduced their prices to attract more customers to their direct offline channels, for which they do not have to pay a commission fee per reservation.

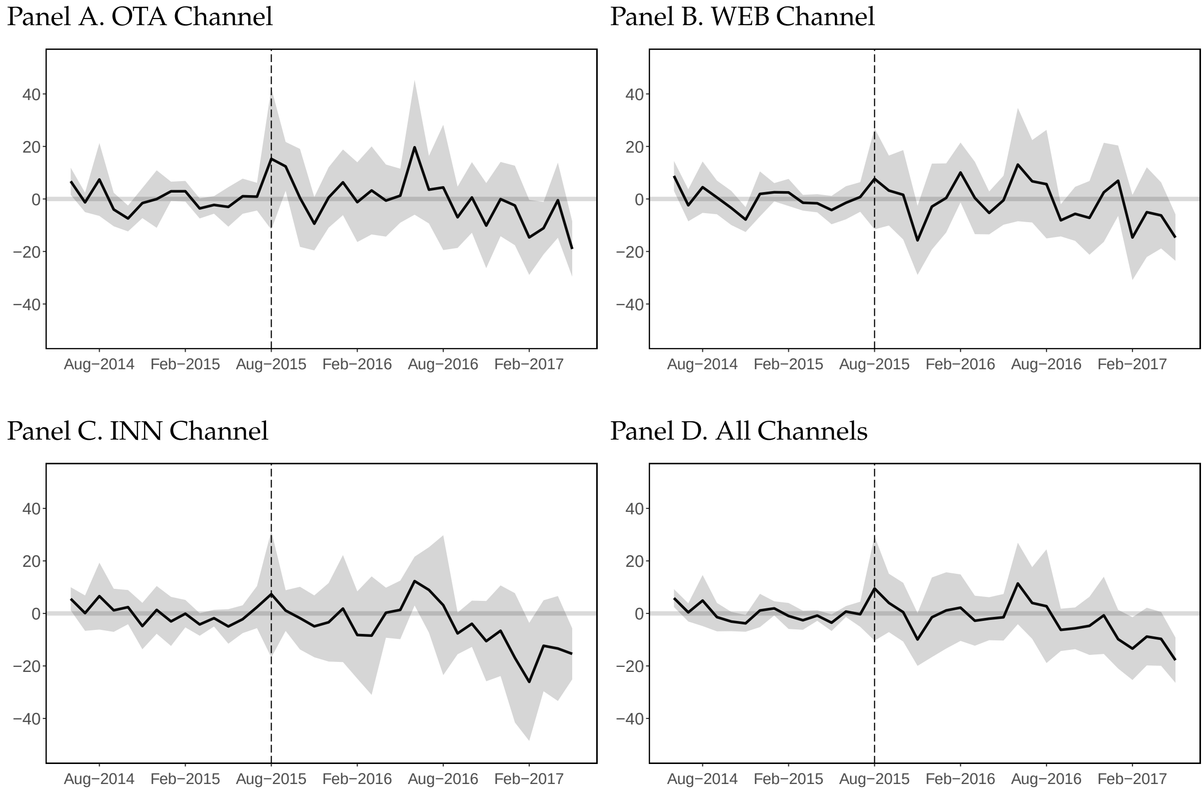


Figure O.3: MC-NN Analysis of Prices — Occupancy Rate Less Than 65%

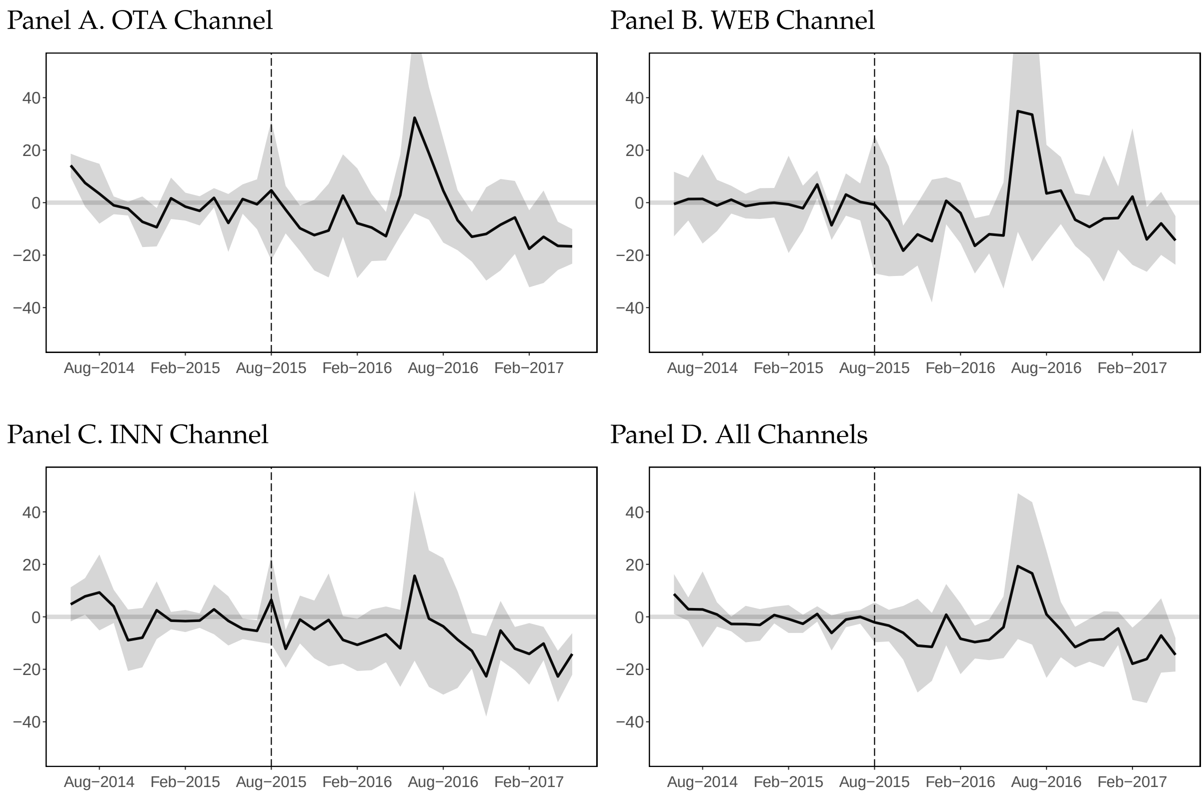


Figure O.4: MC-NN Analysis of Prices — Occupancy Rate More Than 65%

O.4 Heterogeneous Price Effects: Hotel Star Ratings

Table O.4 reports the MC-NN estimation of the price effects by star rating. The relative event study plots are in Figure O.5.

Table O.4—Heterogeneous Price Effects: Hotel Star Ratings

	3 Stars (1)	4 Stars (2)	5 Stars (3)
	Dependent Variable: Log Price × 100		
$\tau^{\text{MC-NN}}$	-2.028	-2.853	-6.207^{***}
	(3.013)	(2.705)	(1.946)
Year-Month FE	✓	✓	✓
Hotel-Channel FE	✓	✓	✓
Observations	6,668	17,436	5,071
No. of Hotels	36	94	27

Note: This table reports the estimated heterogeneous price effects of the Macron Law across three hotel star-rating categories. The analyses are performed using the MC-NN estimator following Equation (5). Year-Month FE (γ_t) indicates the year-month fixed effects. Hotel-Channel 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

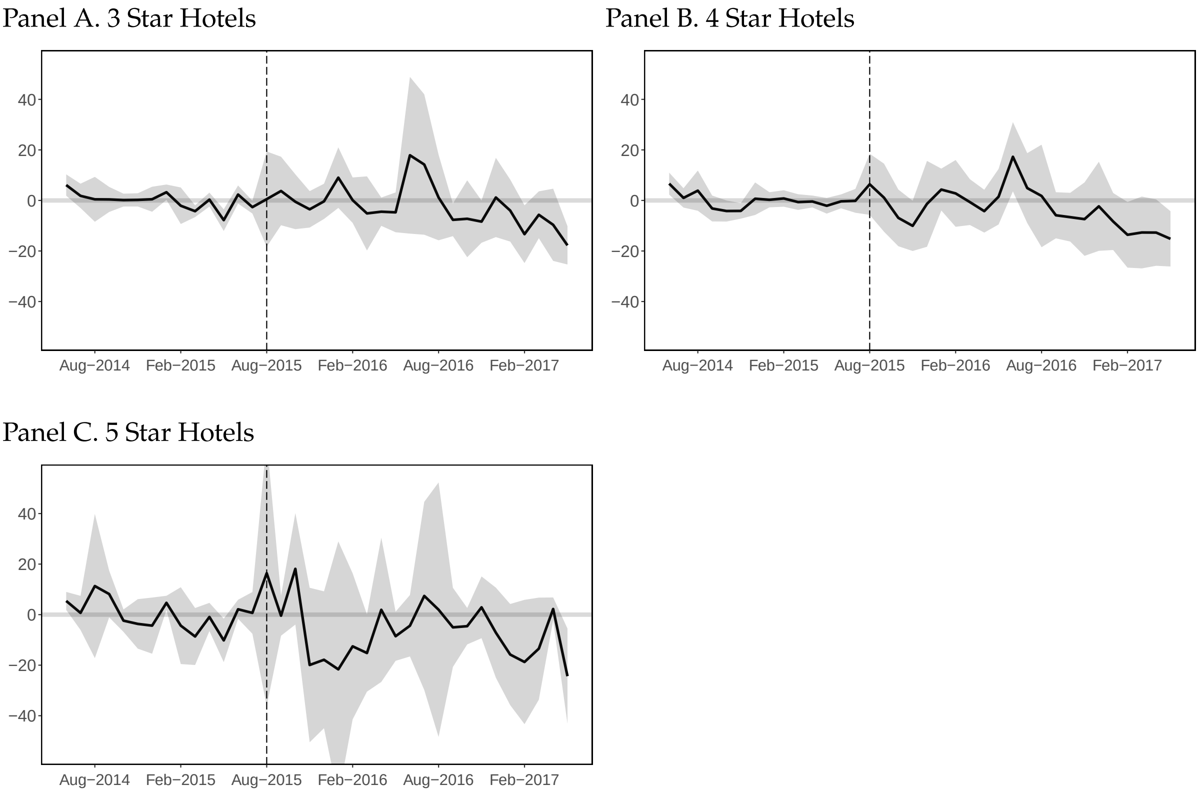


Figure O.5: Heterogeneous Price Effects — Hotels by Star Ratings

P Additional Information on the Implications for Consumer Welfare

Table P.1 presents the number of 3- to 5-star hotels in France in 2017 (Direction Générale des Entreprises, 2022). Since hotel numbers have remained relatively stable following the Macron Law of August 2015, these figures provide a reasonable approximation: about 6,000 3-star hotels and 2,000 4- and 5-star hotels in France.

Table P.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 ΔCS for the population of French hotels in Table 7, we first calculate the bounds of ΔCS for a representative hotel of our sample (Table P.2) and apply the appropriate scaling factor. This factor is the ratio between the average occupancy rate of hotels in our sample and and that of the overall population, to account for the fact that our sample hotels have, on average, higher occupancy rates. We then multiply the scaled ΔCS of the representative hotels in each star category by the corresponding number of hotels reported in Table P.1 to obtain the values in Table 7.

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

	Varian Lower Bound (1)	Varian Upper Bound (2)
3-Star	29,483	37,398
4-Star	178,074	210,144
5-Star	496,032	571,437
Overall	703,589	818,979

Note: This table reports the estimated relative gains in consumer surplus of the Macron Law, comparing changes between France and the control countries for the 22 months after the legislation covered by our sample. The gains refer to the direct offline channel, which experienced statistically significant price reductions after the reform. Bounds are calculated following the procedures proposed by Varian (1985) and calculated using equation (7). Units are in euros.