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Peiyao Ma, Andrea Mantovani, Carlo Reggiani, Annette Broocks and Nestor Duch-Brown

Toulouse School of Economics

The Price Effects of Banning Price Parity Clauses in the EU: Evidence from International Hotel Groups*

Peiyao Ma † Andrea Mantovani ‡ Carlo Reggiani §
Annette Broocks¶ Néstor Duch-Brown ‖

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Abstract

Dominant platforms such as Booking.com and Amazon often impose Price Parity Clauses to prevent sellers from charging lower prices on alternative sales channels. We provide quasi-experimental evidence on the full removal of these price restrictions in France in 2015 for three major international hotel groups. Our analysis reveals a limited and non-significant effect on room prices. The external validity of this finding is established by focusing on similar policy interventions in Germany in 2016 and Austria in 2017. Our results imply that the prohibitions of Price Parity Clauses turned out to be ineffective in sizeably reducing final prices for consumers.

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

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†University of Oxford, Oxford, UK. Email: peiyao.ma@economics.ox.ac.uk.

‡TBS Business School, Toulouse, France and Toulouse School of Economics, 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.

¶European Commission, Joint Research Centre, Seville, Spain; Annette.BROOCKS@ec.europa.eu.

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

1 Introduction

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

Controversial arrangements at the center of regulatory scrutiny are Price Parity Clauses (PPCs), namely price restrictions imposed by platforms on client sellers, stipulating 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 require that the price charged by sellers cannot be lowered on *any* alternative sales channel. The "narrow" PPCs are less rigid, allowing sellers to reduce the price on rival platforms, but they cannot offer lower prices when selling directly.

Platforms affirm PPCs are necessary to prevent showrooming, whereby consumers consult the platform to find 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 their activity unprofitable, possibly undermining their existence. Conversely, competition authorities and regulators claim that PPCs reinforce the dominant position of leading platforms by raising entry barriers, therefore increasing prices for consumers. Indeed, if sellers cannot differentiate prices, consumers would be more likely to buy through the platforms, which usually offer additional benefits. The platforms can then set a relatively high commission fee and extract a large portion of the sellers' profits. Contrarily, if PPCs were removed, the sellers could lower prices when selling directly, thereby limiting the platforms' ability to charge excessive fees.

This article focuses on the lodging sector and investigates the price effects of removing all types of PPCs. We exploit policy changes that occurred in the EU between 2015 and 2017, especially in France, Germany, and Austria. Our exhaustive and unique dataset covers three years, from July 2014 to June 2017, and consists of monthly transaction data for 200 hotels belonging to three major international groups. These hotels span 74 cities in 9 European countries and employ multiple channels to sell their rooms, among which are major OTAs.

We employ quasi-experimental methods to empirically estimate whether or not the hotels in our sample decreased their prices following the full removal of PPCs in France in 2015, compared with other EU countries in which narrow PPCs were still allowed. Estimates of standard and synthetic difference-in-differences (DID) show statistically non-significant price effects on OTAs and hotel websites, ranging between -0.432% and -1.028% for our benchmark specification. Qualitatively similar estimates are obtained using Matrix Completion for the PPC bans in Germany and Austria in 2016, vouching for the external validity of our results. In contrast with the expected outcome, our findings suggest the policy changes did not produce significant price reductions.

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

PPCs remain a central issue of interest for policymakers dealing with the challenges posed by dominant digital platforms, with an explicit *ex-ante* ban of these contractual provisions currently being discussed. In May 2021, the German Federal Court of Justice ruled that narrow PPCs violated antitrust laws, thus confirming the decision of the Federal Cartel Office in 2015 to prohibit all types of PPCs. In November 2021, the UK CMA recommended that wide PPCs be included in the list of hardcore restrictions in revising the Vertical Agreements Block Exemption regulation (Marshall, Albrighton and Kim, 2021). In addition, the Digital Markets Act (DMA) proposed by the European Commission prohibits very large platforms from using all types of PPCs (Cabral et al., 2021).

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

Recent empirical contributions, however, do not provide conclusive evidence. On the one hand, Hunold et al. (2018) and Ennis, Ivaldi and Lagos (2020) found 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 any form of PPCs for Booking.com in 2015. The latter focuses on the cheapest channel in 2014 and 2016, using data from the EU and worldwide to study 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 of 2015. Moreover, an investigation of the hotel booking sector in Germany in 2020 (Bundeskartellamt, 2020) showed that the elimination of narrow PPCs did not produce the expected reduction of the commission fees charged by platforms. Finally, Mantovani, Piga and Reggiani (2021) examined the effect of the full removal of PPCs in France in 2015, and found a limited response of prices posted by hotels on Booking.com, both in the short and medium run. They showed, however, that chain hotels displayed a more pronounced price reaction.

Summing up theoretical and empirical findings, there is still a degree of uncertainty regarding the actual effects on hotel prices of the policy changes introduced in different EU countries over the past years (Argenton and Geradin, 2022). It seems that more organized units, such as chain hotels, could have benefited from the prohibition of PPCs. In contrast, small and independent hotels may find it more difficult to break free from the influence of dominant platforms.

This article reports novel empirical estimates of the price effects of removing PPCs. We focus on France, the first country to prohibit all types of PPCs in the lodging sector. Our dataset enables us to investigate similar interventions that occurred in Germany and Austria after the French one. However, as these ensuing policy changes could have been anticipated by OTAs, we utilize them to investigate the external validity of our main findings.

We extend beyond the previously discussed articles in three ways. First, we exploit a uniquely detailed proprietary database with channel-level transaction information provided by three major international hotel groups. Second, our data allows us to measure the price changes across different sales channels, rather than the probability that the direct channel is the cheapest. Third, we employ recently developed estimators from the DID and Machine Learning literature. Our analysis shows that banning PPCs did not affect the hotel prices in our sample, and this result proves to be robust for a number of specifications and estimation techniques. Our finding is remarkable as we specifically focus on large hotel groups, the most likely winners from the policy change, given their presumably stronger position *vis-à-vis* dominant OTAs.

There may be several reasons for this finding. Sellers, even when affiliated with large chains, may still be hesitant to differentiate prices, as they may be penalized otherwise. Hunold, Kesler and Laitenberger (2020) show OTAs downlist hotels that set lower prices elsewhere, a practice called "dimming". The authors also observe that chain hotels usually rank better as they have more offers available on OTAs. Hence, one may conjecture they would suffer more from downlisting than independent structures. Peitz (2022) suggests that platforms can simply adjust their recommendation algorithms to increase the visibility of hotels that generate higher conversion rates from consumer queries. This is because low conversion rates are generally associated with hotels that offer more attractive prices outside the platform. The creation of preferred partner programs (PPPs), in which price parity is the counterpart for top-listed sellers, could also represent a response from OTAs to the ban of PPCs (Cazaubiel et al., 2022).

Overall, dominant OTAs seem to have found ways to convince sellers to provide the most appealing offers on their platforms, even without a formal contractual obligation. Therefore, the prohibition of PPCs might have turned out to be ineffective. This issue is not specific to the lodging sector, but it occurs more generally, as exemplified by Amazon's tactic to remove the "Buy Box" option for those products with lower prices offered elsewhere (Hunold, Laitenberger and Thébaudin, 2022). In addition, the accelerated digitization caused by the COVID-19 pandemic suggests that platforms may now control an ever-growing market share. In this context, our study supports the view that additional provisions should be included in regulations aiming to counter the dominant position of large players, in order to render the platform structures more transparent and competitive.

2 Data

Our empirical analysis is based on transaction data of 200 individual hotels from 74 cities in 9 European countries. These hotels are from 18 chain hotel brands belonging to three major international hotel groups. Our sample covers a three-year period, from July 2014 to June 2017. An observation in the data is a unique hotel/month/distribution channel combination. Each observation features the number of transactions, the reservation channel, the revenue generated through each channel, and the number of room nights being sold. Room night is a standard statistical metric in the hotel industry. At the hotel level, further information is available about the star rating, the number of hotel rooms, and additional hotel features and amenities (restaurant, bar, spa, etc.).

This study focuses on the two online channels, Web Direct (WEB) and Online Travel Agency (OTA), which are directly affected by the initial imposition and subsequent prohibition of PPCs. As our dataset includes both online and offline booking channels, we calculate the shares of such channels over the total reservations made. Additional information about the data can be found in Online Appendix A.

Table 1 reports the summary statistics for the main variables in our dataset. The information is provided for individual countries and overall. During our sample period, France, Germany, and Austria experienced policy changes related to PPCs. We index the treatment status T of a country by the month that it implemented the policy change. There are 36 months in our sample, and T is set to infinity for the six never-treated countries, which are the controls.

The average hotel is rated 4 stars and has a capacity of approximately 210 rooms. On average, 4230 room nights per month were sold by each hotel, with the WEB channel accounting for 16.6% of the total, and the OTA channel, 18.1%. The average price of a room reserved through a hotel's website is 140.92 EUR and 136.83 EUR if booked through an OTA. For both channels, one may also notice that prices in France are somewhat higher than the sample average. Conversely, prices in Austria and Germany align with the overall mean. These differences will play an important role in our empirical strategy.

3 Empirical Strategy

We exploit a major legislative change in the hospitality sector to provide evidence on the price effects of prohibiting PPCs. On August 6th, 2015, France enacted the "Macron Law," thus becoming the first country in the world to ban all types of PPCs imposed by OTAs on affiliated hotels (Roskis and Strange, 2015). We also consider two related but ensuing events to assess the external validity of our analysis: (i) the German Competition Authority's decision to prevent Booking.com from using PPCs, starting February 2016 (Bundeskartellamt, 2015); (ii) Austria's amendment to the law on unfair competition that prohibited all types of PPCs starting November 2016 (European Competition Network, 2017, pp.4-5). According to competition authorities and the discussed economics literature, eliminating PPCs should significantly lower hotel prices, especially in the direct online channel.

Table 1—Summary Statistics of Hotel Characteristics By Country

	Star Rating	Hotel Capacity	Room Nights	Price WEB	Price OTA	Share WEB	Share OTA
France	4.10	172.67	3220	179.63	178.85	16.9%	16.2%
(n = 4037, T = 14)	(0.62)	(104.9)	(2347)	(82.86)	(103.2)		
Germany	4.10	289.97	6233	150.40	139.97	15.4%	19.7%
(n = 5487, T = 20)	(0.98)	(158.4)	(4065)	(65.1)	(58.55)		
Austria	4.36	212.45	3900	135.94	135.12	14.5%	16.4%
(n = 2044, T = 29)	(0.50)	(160.5)	(3849)	(58.01)	(56.27)		
Control	3.91	199.05	3985	127.15	122.86	17.3%	17.7%
(n = 21482, $T = \infty$)	(0.61)	(138.9)	(3456)	(74.44)	(76.19)		
Belgium	3.61	160.33	2919	125.41	115.04	17.3%	19.1%
(n = 3141, $T = \infty$)	(0.61)	(87.62)	(1945)	(37.21)	(34.94)		
Italy	4.03	196.8	3728	135.42	132.50	15.6%	16.0%
(n = 5373, $T = \infty$)	(0.49)	(113.7)	(2729)	(74.32)	(77.85)		
Netherlands	4.10	195.35	4032	168.75	169.40	15.7%	19.3%
(n = 3831, $T = \infty$)	(0.72)	(103.8)	(2848)	(118.55)	(131.8)		
Portugal	4.06	161.38	3096	117.08	116.71	12.7%	17.0%
(n = 2961, $T = \infty$)	(0.68)	(53.87)	(1682)	(79.11)	(80.71)		
Spain	3.76	173.71	3287	100.23	100.72	16.2%	11.8%
(n = 3688, $T = \infty$)	(0.62)	(96.54)	(2202)	(47.10)	(53.14)		
United Kingdom	3.97	254.91	5648	142.29	135.06	20.0%	20.5%
(n = 6319, $T = \infty$)	(0.63)	(203.8)	(5003)	(93.41)	(94.66)		
Overall	4.00	209.83	4230	140.92	136.83	16.6%	18.1%
(n = 36881)	(0.64)	(139.9)	(3525)	(81.29)	(86.17)		

Note: This table reports the mean hotel characteristics of each country, as well as the overall mean. Standard deviations are reported in parentheses. In the dataset, France, Germany, and Austria experienced treatments at different periods. The treated countries are identified by their respective treatment time T, which indicates the number of months since July 2014. The never-treated countries are denoted with treatment time equal to infinity and serve as controls. Star Rating reports the average number of star ratings. Hotel Capacity denotes the average number of rooms. Room Nights represents the average monthly room-night sales of the hotels. The "Price" columns report the average prices of rooms sold through the WEB and OTA channels, respectively. The "Share" columns report the percentages of rooms sold through the WEB and OTA channels, respectively.

Difference-in-Differences. For our identification strategy, we exploit the time dimension of our dataset by considering the monthly hotel prices *before and after* the Macron Law of August 2015. French hotels are the *treated* group, whereas hotels in the never treated countries constitute the *control* group. Due to the Paris terrorist attacks on November 13th 2015, which produced a lingering and negative demand shock for accommodations in the French capital (Insee, 2016, Table 1), we provide estimates that both exclude and include hotels in Paris.

Our benchmark analysis hinges upon a two-way fixed effect (TWFE) DID regression design:

$$\ln(p_{it}) \times 100 = \tau^{\text{DID}} M_{it} + \gamma_t + \delta_i + \rho R_{it} + \varepsilon_{it}, \tag{1}$$

where i identifies a unique hotel-channel combination, and t denotes the month. The outcome variable $ln(p_{it}) \times 100$ is the natural logarithm of the monthly average channel price multiplied by 100, for an easier interpretation of the results. The variable δ_i is a hotel fixed effect, and γ_t is a cumulative monthly dummy variable to account for seasonality. The term M_{it} equals 1 if unit i in month t is "treated" by the Macron Law. The monthly room sales control, R_{it}, contains information regarding the average room nights sold for unit i in month t, and ε_{it} is the error term. The coefficient of interest is τ^{DID}, which captures the DID effect, namely, the percentage change in prices in France *vis-à-vis* the control group after the removal of PPCs.

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

Second, we assume that there are no anticipation effects in all pre-treatment periods. As regulatory interventions are announced before promulgation, we formally consider this issue when discussing the results.

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

$$\ln(p_{it}) \times 100 = \sum_{t=-13,\ t\neq-1}^{22} \beta_t D_{it} + \gamma_t + \rho R_{it} + \delta_i + \varepsilon_{it}, \tag{2}$$

where the dummy variables D_{it} switch on if the Macron Law is t months away and if unit i is treated. The variable δ_i is a hotel fixed effect, and γ_t is the month fixed effect. The monthly room sales control R_{it} contains information about the average room nights sold for unit i in month t. The error term is ε_{it}. By convention, the outcome of period -1 is normalized to 0.

Finally, to tackle the well-known issues of biased standard errors in DID models (Bertrand, Duflo and Mullainathan, 2004), we follow Angrist and Pischke (2008) and cluster the standard errors for both Equations (1) and (2) at a higher level of aggregation, namely, the city.

Synthetic Difference-in-Differences. Our baseline DID specification implicitly imposes uniform weights on all control units. We then relax such an assumption by employing the synthetic difference-in-difference (SDID) method to estimate the average treatment effect (Arkhangelsky et al., 2021). SDID allows us to gain further insights into the appropriateness of the previously used control group and the parallel trends assumption.

More in detail, SDID assigns weights to control units to match those in the treated units as the canonical Synthetic Control Method (SCM, see Abadie, 2021), but there are also time weights. Furthermore, the canonical SCM requires the weights assigned to "donors" to be between zero and one to match the treated group as closely as possible. However, as the hotel prices in France are higher than those in all control countries, as shown in Table 1, it would be impossible to implement SCM due to the infeasibility of a synthetic control with such properties.

To sum up, SDID not only relaxes the constraints imposed on weights but also synthesizes pre-treatment parallel trends by assigning different weights to the selected donors and periods. As SDID requires a fully balanced panel, we aggregate the hotel-level observations to the country-level and use never-treated countries as potential donors. The main parameter of interest is calculated as:

$$\hat{\tau}^{\mathrm{SDID}} = \underset{\tau,\delta,\gamma,\rho}{\arg\min} \left\{ \sum_{i=1}^{7} \sum_{t=1}^{36} \left[\ln\left(p_{it}\right) \times 100 - \tau M_{it} - \gamma_t - \delta_i - \rho R_{it} - \varepsilon_{it} \right]^2 \hat{\omega}_i \hat{\lambda}_t \right\}, \tag{3}$$

where we minimize the weighted sum of residuals of a specification based on countries (n = 7, France and never-treated countries) and months (n = 36). The parameters $\hat{\omega}_i$ and $\hat{\lambda}_t$ denote the weights of donor countries and time periods, respectively.

External Validity. Apart from the first policy intervention by France in August 2015, Germany and Austria also experienced similar changes in February 2016 and November 2016, respectively. As previously discussed, the institutional setting in which the removal of PPCs occurred was rather heterogeneous between those countries. Notwithstanding the differences, these three interventions had the common character of removing PPCs from major OTAs. Consequently, we consider these policy changes as staggered adoptions of a single treatment.

We jointly evaluate the price effects of these policy changes by adopting the Matrix Completion-Nuclear Norm (MC-NN) method developed by Athey et al. (2021). MC-NN originates from forecasting tasks in Computer Science and adopts Machine Learning techniques to predict the "potential outcomes" of treated units. Potential outcomes refer to the unobserved outcome of the treated units in the counterfactual case that they are not treated (Imbens and Rubin, 2015). MC-NN combines information on the control and treated units' pre-treatment patterns to impute the treated units' counterfactual outcome after a given intervention. The treatment effect is then calculated by subtracting the treated units' potential untreated outcomes from those that are observed.

Similarly to SCM and SDID, the MC-NN method synthesizes a parallel pre-treatment trend by assigning weights to only the most appropriate control units. One advantage of MC-NN, compared to those alternative methods, is that it accommodates unbalanced panels, which enables us to utilize our full, uncollapsed dataset. MC-NN is also suited to estimate staggered treatment effects and allows for time-varying controls.

Technically, the main specification follows the form:

$$\mathbf{Y} = \mathbf{L}^* + \Gamma^* \mathbf{1}_T^\top + \mathbf{1}_N (\Delta^*)^\top + R_{it}^\top \rho + \boldsymbol{\varepsilon}, \tag{4}$$

where $\mathbf{Y}$ is the complete outcome matrix of the natural logarithm of monthly hotel price multiplied by 100. This matrix features both the observed outcomes and the counterfactual ones. $\mathbf{L}^*$ denotes the low-rank $N \times T$ matrix of counterfactuals that we estimate. $\Gamma^* \in \mathbb{R}^{N\times 1}$ represents the hotel fixed effect, and $\Delta^* \in \mathbb{R}^{T\times 1}$ denotes the time fixed effect. We also include the time-varying covariate R_{it} to account for average room nights demand for hotel i in cumulative month t. The error vector is ε.

4 The Price Effects of Removing PPCs

Figure 1 plots the event study analysis of Equation (2) by showing the percentage differences in prices between France and the control group. The plot shows that none of the differences before the treatment are significantly different from zero. This suggests satisfactory pre-treatment parallel trends and attests to the suitability of our chosen control group for both the WEB and OTA channels, particularly considering the span and diversity of our sample.

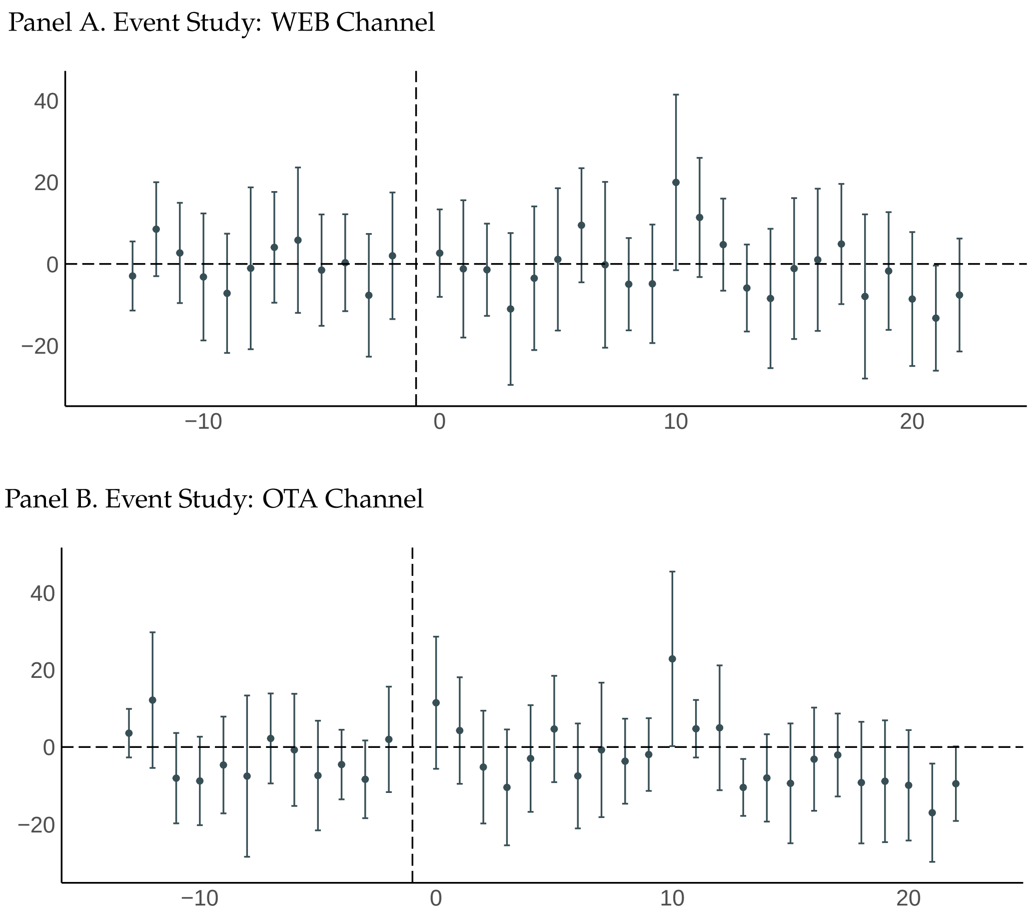

Figure 1: Event Study of the Macron Law — France vs Control

Difference-in-Differences. Table 2, Panel A reports the estimated TWFE DID coefficients of Equation (1). Our preferred specifications, which appear in Columns (1) to (4), exclude Paris in the treatment group and compare the hotel prices of other French cities to those in the control group. As mentioned above, Paris hotels were removed from our baseline analyses due to concerns that the 2015 terrorist attacks, which occurred three months after the Macron Law, may have confounded the price effects of the latter.

Columns (1) and (2) report the estimated price effects of the Macron Law for the WEB and OTA channels, respectively. The DID coefficient (τ^{DID}) indicates a -0.934% decrease in room prices on the French hotel websites after the prohibition of PPCs. The estimated coefficient for OTAs indicates an even smaller decrease of -0.432%. Both coefficients, however, are not significantly different from zero.

Table 2—Estimated Price Effects of Prohibiting PPCs: Main Results

	Dependent Variable: Log Price × 100							
	Excluding Paris				Including Paris			
	WEB (1)	OTA (2)	WEB (3)	OTA (4)	WEB (5)	OTA (6)	WEB (7)	OTA (8)
Panel A. TWFE Results								
τ^{DID} (Macron Law)	−0.934	−0.432	−1.028	−0.541	−3.231	−3.677	−2.674	−3.142
	(2.011)	(2.240)	(1.967)	(2.304)	(2.494)	(3.071)	(2.125)	(2.731)
Room Nights (ρ)			0.004	0.004			0.004	0.004
			(0.001)	(0.001)			(0.001)	(0.001)
Months FE	✓	✓	✓	✓	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,222	5,209	5,222	5,209	5,434	5,421	5,434	5,421
Panel B. SDID Results								
τ^{SDID} (Macron Law)			−0.747	−0.806			−1.895	−0.074
			(3.954)	(2.795)			(3.958)	(2.823)
Room Nights (ρ)			0.010	0.011			0.010	0.011
			(0.003)	(0.003)			(0.003)	(0.003)
Observations			252	252			252	252
Panel C. MC-NN Results								
Treated vs Control			1.371	0.733			0.313	−0.649
			(1.923)	(2.064)			(1.994)	(2.321)
Room Nights (ρ)			0.004	0.004			0.004	0.004
			(0.001)	(0.001)			(0.001)	(0.001)
Months FE			✓	✓			✓	✓
Hotels FE			✓	✓			✓	✓
Observations			6599	6585			6811	6797

Note: This table reports the estimated price effects of prohibiting PPCs. The WEB and OTA column headers indicate the coefficients estimated using subsets of data from the WEB and OTA channels, respectively. For robustness, we report the estimates when Paris is excluded and included in the treatment group. Panel A reports the TWFE DID results estimated using Equation (1). Robust standard errors are clustered at the city level and reported in parentheses. Panel B reports the SDID estimates using Equation (3). The hotel-level observations are aggregated to the country level, as SDID requires a perfectly balanced panel. Panel C reports the external validity of our results using Equation (4). Room Nights (ρ) indicates estimated coefficients of the monthly room nights sales variable. Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotels fixed effects.

Columns (3) and (4) show these effects when accounting for a time-varying control, the monthly average of room nights reserved. Adding a time-varying control does not substantially affect the estimated τ^{DID}, which results in -1.028% for WEB and -0.541% for OTA. Even though the estimated coefficients for the control variable ρ are highly significant, the DID coefficients of interest are not significantly different from zero.

While the standard errors of the estimated τ^{DID} in columns (1) to (4) are relatively large, this is a common issue also for datasets analyzed in the related literature. Based on the results from our benchmark specification and with 95% confidence, we can rule out price effects greater than -5%. While this may seem high compared to our point estimates, we note it is still substantially lower than the commission fees imposed by OTAs, which are usually 15%.

These results do not appear to be fully in line with our expectations. On the one hand, our estimates point to a higher price decrease on the hotel direct channel (WEB) than on OTAs. On the other hand, all of these effects are very small in magnitude and insignificantly different from zero. Recall that both the policymakers and the majority of researchers suggested that a significant price decrease should follow the prohibition of all PPCs. These predictions, however, do not seem to hold when we analyze the Macron Law, the very first intervention in the EU.

In Columns (5) to (8), we perform the same estimations but also include observations for Parisian hotels. These results qualitatively confirm the above findings of a negative but statistically non-significant decrease in French hotel prices compared to the control group. Notice, however, that the magnitude of the effects is more pronounced for both WEB and OTA (with coefficients ranging between -2.674% and -3.677%). These coefficients, albeit not the main focus of our paper, demonstrate that in the months following the Macron Law, hotel prices did not significantly decrease, even in the presence of an additional confounding negative shock.

We now move beyond the baseline analysis and assess the robustness of our main findings in several directions. First, as the Macron Law was approved by the French Parliament between June and July 2015, we consider the possibility of anticipatory effects in Online Appendix B. The results show that the small and not statistically significant treatment effects persist even if we allow for one or two months of anticipation from both hotels and platforms.

Second, in Online Appendix C, we perform a placebo test for our benchmark results. Drawing inspirations from the SCM literature Abadie (2021), we randomly assign treatment status to hotels in any country and perform the analysis 1000 times. Comparing our results in Table G.1, Panel A, Columns (3) to (4) with the distribution of estimated placebo τ^{DID}, we show that our non-significant estimates could have reasonably resulted from a random sample for both WEB and OTA.

Third, in Online Appendix D, we explore the heterogeneity in treatment effects for hotels of different star ratings and sizes. We find that the treatment effect is rather homogeneous across hotels of 3, 4, and 5 stars. Whereas there are differences in the magnitudes, all estimated effects are not significantly different from zero. As for hotel size, most estimated coefficients are small and insignificant, except for large hotels on the WEB channel. However, this result may be driven by low statistical power due to the scarce number of observations.

Fourth, in Online Appendix E.1, we present the event study plots for TWFE and three newly-developed estimators. The recent literature has thoroughly investigated the potential bias in TWFE DID estimators, particularly in the context of staggered treatment timing and heterogeneous treatment effects (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak, Jaravel and Spiess, 2022; Gardner, 2022). Graphical evidence in Figure E.1 confirms the validity of our baseline TWFE specification and verifies that the Macron Law had no significant impact on the room prices of French hotels.

Finally, one may wonder whether the ban on PPCs had any effect on the prices of other sales channels. While this is not the focus of our paper, in Appendix F, we show that almost all channels did not register a significant price reduction, except Wholesale, which only accounts for 1.7% of the total transactions.

Synthetic Difference-in-Differences. Table 2, Panel B, reports the estimated price effects using SDID from Equation (3). Similar to DID, we carry out the estimations both excluding and including Paris. We note that SDID requires aggregating the data, but, at the same time, it is robust to the inclusion of time-varying covariates. Therefore, in Columns (3)-(4) and (7)-(8), we present the estimated coefficients τ^{SDID} including such a covariate, as these specifications achieve a better fit in the pre-treatment period given the limited number of observations.

When excluding Paris from the treatment group, the coefficients in Columns (3) and (4) indicate that, after the Macron Law and relative to the synthetic control, French hotels decreased their room prices by -0.747% on their websites and by -0.806% on the OTAs. As in baseline DID, these effects are small and statistically non-significant. When including Paris, the coefficients in Columns (7) and (8) still indicate a limited price reduction (-1.895% on WEB and -0.074% on OTA, respectively). Online Appendix G provides more detail for these results.

Figure 2 provides a graphical illustration of the SDID estimates. Note that the trajectories of France and the Synthetic Control are relatively similar throughout the observed periods. The similar dynamics of the treatment and synthetic control trends suggest that the Macron Law did not lead to any substantial hotel price reductions on either the WEB or OTA channel. Overall, the SDID methodology confirms the findings of our benchmark DID analyses, both in terms of magnitude and statistical non-significance.

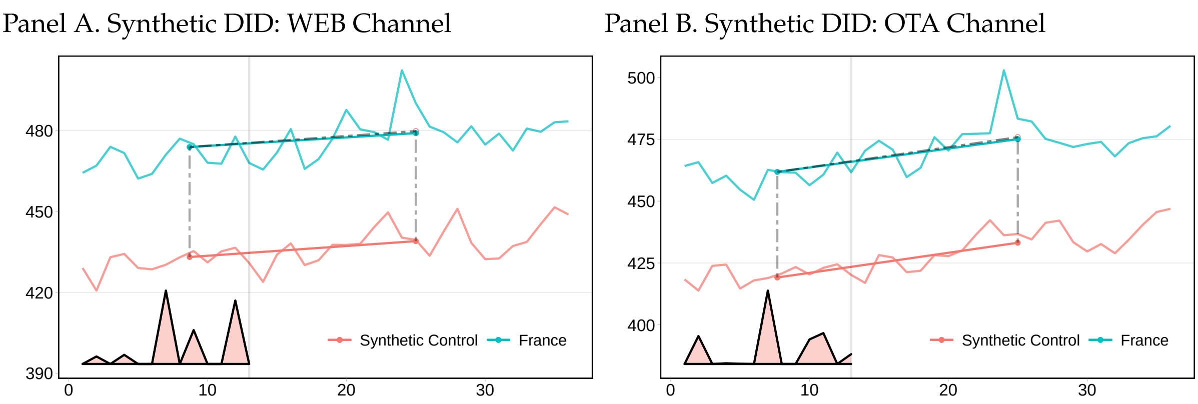

Figure 2: Synthetic Difference-in-Differences — France vs Synthetic Control

External Validity. Finally, it is important to assess whether these statistically non-significant findings are unique to French hotels or are likely to hold more generally. To address this issue, Table 2, Panel C reports the estimated joint effects of the interventions in France, Germany, and Austria between 2015 and 2017 compared to the control group. To take full advantage of MC-NN's robust estimation procedure and in the light of better pre-treatment fit, we focus on the specifications with the time-varying covariate and report the coefficients in Columns (3)-(4) and (7)-(8).

When we exclude Paris in our analyses, we find statistically non-significant price effects of 1.371% on WEB and 0.733% on OTA. Qualitatively similar results are obtained when including Paris, with the coefficients becoming 0.313% and −0.649%, respectively. We also report the individually-estimated coefficients for the French, German, and Austrian policy changes in Online Appendix H, all of which are statistically non-significant.

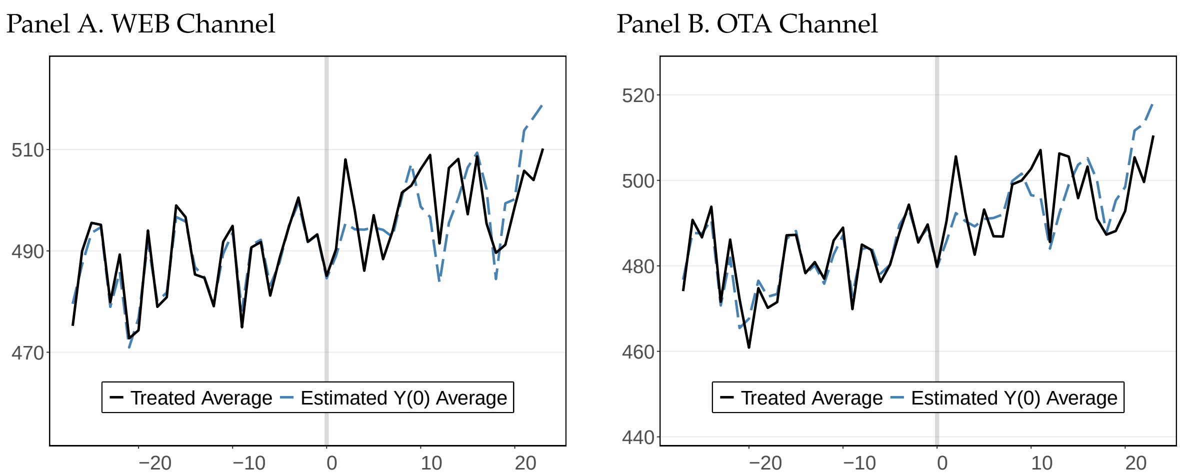

Figure 3: External Validity — Treated Countries vs Counterfactual Averages

Figure 3 graphically illustrates the non-significant joint effects of these staggered treatments across three countries. Note that the trends between the treated average and counterfactual average are mostly identical, with only differences in residual seasonality towards the end of the observed periods. Similar graphical evidence using estimators developed by Callaway and Sant'Anna (2021), Sun and Abraham (2021), Borusyak, Jaravel and Spiess (2022) are reported in Online Appendix E.2.

While the positive coefficients may seem surprising and counter-intuitive, we hypothesize that the effectiveness of the German and Austrian legislation was substantially weakened compared to that of the Macron Law due to the countermeasures adopted by dominant OTAs in response to the prohibitions of PPCs, as highlighted in Section 1. Since large platforms operate globally, it would be natural for them to incorporate defensive mechanisms after the Macron Law, which was the least anticipated legislation, and apply them to markets where such policy changes have yet to occur.

Overall, our MC-NN estimates indicate that the prohibition of PPCs, which took place in France, Germany, and Austria during the period covered by our dataset, did not lead to significant price reductions.

5 Discussion

This article provides a thorough empirical assessment regarding the price effects of policy interventions that banned PPCs in the lodging sector, a fundamental issue that was only partially addressed by previous contributions. We relied upon unique proprietary data on prices charged in the EU by three leading international hotel groups. Our data include all sales channels between 2014 and 2017, a period characterized by important policy changes.

The main event that we considered is the Macron Law, which prohibited PPCs in France in August 2015. Both standard and synthetic DID analyses showed statistically non-significant price effects from hotel websites and OTAs. These results are robust when we account for anticipatory reactions and heterogeneous treatment effects, and when we employ recently proposed estimators from the DID literature. Moreover, the external validity of our findings is confirmed when taking into account similar interventions in Germany and Austria using newly-developed Machine Learning techniques.

The richness of our dataset and the novelty of our methodology enable us to go beyond the extant literature in several ways. The study of Hunold et al. (2018) was based on indirect evidence about hotels in different countries collected by the metasearch engine Kayak. Ennis, Ivaldi and Lagos (2020), similar to us, relied on actual transaction data for chain hotels operating across countries in the EU and the rest of the world. Both studies, however, focused on the probability that the direct channel displayed the lowest price. Mantovani, Piga and Reggiani (2021) provided quasi-experimental evidence by employing data scraped from Booking.com. They did not, however, observe the direct channel, and only relied on prices posted online.

Remarkably, our main findings are inconsistent with the expected price reduction that should follow the prohibition of restrictive practices such as PPCs. Indeed, economic theory predicts that removing PPCs should lower commission fees, therefore reducing final prices for consumers (Boik and Corts, 2016; Wang and Wright, 2020; Calzada, Manna and Mantovani, 2022). This was one of the arguments motivating regulators and policymakers to ban PPCs. However, we demonstrate that a relevant price reduction did not occur in our considered setting.

There may be several reasons for the limited and non-significant response of the hotels in our sample. For example, a survey in European Competition Network (2017) has documented a scarce awareness of hoteliers regarding these policy changes. Half of them did not know that OTAs had changed their parity clauses in the previous year. This explanation may not hold in our scenario, given that we consider chain hotels belonging to large groups, whose management is likely to be well-informed about the latest developments in the sector.

More coherent with our setting, and in general with our analysis of the sector, is the consideration that OTAs seem to have elaborated a set of strategies that achieved similar outcomes as PPCs. On the one hand, retaliatory practices, such as the previously explained "dimming" (Hunold, Kesler and Laitenberger, 2020), acted as a deterrent for price differentiation by hotels. In fact, OTAs kept monitoring the hotel pricing strategies through rate checker software and contacted them regarding eventual parity violations (for an example, see Appendix I). On the other hand, platforms reinforced collaboration ties with those hotels that respect their provisions, rewarding them with better listings, enhanced services, and recommendation systems that serve such purpose (Peitz, 2022). Taken together, these strategies could represent an effective way to circumvent the ban on PPCs. Additional theoretical research would be very useful in this respect; to the best of our knowledge, there are no papers explicitly investigating strategic responses adopted by dominant platforms to policy changes.

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

Despite the richness of our dataset, our analysis presents some limitations. First, the OTA channel includes transactions completed on large platforms, such as Expedia and Booking.com, and smaller ones, such as Ctrip or Hotel.de. We cannot, however, distinguish between OTAs, which prevents us from analyzing the differential impact of prohibiting PPCs on specific websites. Furthermore, the literature suggests that removing PPCs may induce the entry of new OTAs (Ezrachi, 2015), but it could lower incumbent platforms' propensity to invest and innovate (Wang and Wright, 2022). Unfortunately, as with the rest of the literature, our data did not allow us to address effects other than price. Finally, precise information about the agency fees was available only for a sub-sample of hotels, therefore we were not able to include them in our econometric analysis. Nonetheless, our partial data indicate that, throughout the 2014-2017 period, the agency fees decreased by about one percentage point, with no significant differences between France and the control group.

Notwithstanding these limitations, our evidence shows that eliminating PPCs alone does not produce sizeable price reductions. 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 fees (Gomes and Mantovani, 2020) and curbing recommendation biases (de Cornière and Taylor, 2019; Teh and Wright, 2020). These additional provisions are likely to play a complementary role in the design of platform regulation to ensure that the benefits of digitization are fairly distributed and shared across all stakeholders.

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

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A 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 Website Direct (WEB) and Online Travel Agencies (OTA). The WEB and OTA channels, respectively, include transactions made on the hotel websites and on platforms such as Booking.com, Expedia, as well as Ctrip and Hotel.de, among others. The offline channels include the Global Distribution System (GDS), Hotel Direct (INN), Wholesale (WHOLESALE), and a residual category for all other offline bookings (OTHER).

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 INN channel is the main offline direct sales channel for hotels. It comprises of direct phone calls, e-mail reservations, walk-ins, as well as bookings from chain-specific call centers. The WHOLESALE channel is unique in that capacities are often offered to travel agencies before the season begins. These rooms may be included in package holidays or sold to other sellers.

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

Channel	2014	2015	2016	2017	Average
Online					
WEB (Web Direct)	15.0	15.9	17.5	18.5	16.6
OTA (Online Travel Agency)	16.1	17.6	18.8	20.2	18.1
Offline					
GDS (Global Distribution System)	12.0	12.3	12.5	13.4	12.5
INN (Hotel Direct)	53.8	51.5	48.8	46.2	50.3
WHOLESALE (Wholesale)	2.3	1.8	1.4	0.9	1.7
OTHER (Other Offline Bookings)	0.9	0.9	1.0	0.9	0.9
Total (%)	100	100	100	100	100

B Anticipation and Delayed Effects

Anticipation of the Macron Law should have negligible effects on French hotel prices. On the one hand, it would be unlikely for the platforms to end their PPCs with hotels prematurely, as this may undermine the attractiveness of the platforms. On the other hand, hotels would be unable to lower the prices on their official websites beforehand, as it would be a breach of the PPCs. Our findings confirm these conjectures. As shown in Panel A of Table B.1, the price effects of shifting the treatment timing by one and two months before the Macron Law are small and non-significant.

We also consider the possibility that the treatment effects might be *delayed*. Mantovani, Piga and Reggiani (2021) observe that there may exist a large gap between the booking date and the check-in date of hotel rooms. In other words, the rooms booked after the Macron Law may take weeks before they are checked in. To account for such a delayed effect, we shift the treatment timing by one and two months after the Macron Law. As shown in Panel B of Table B.1, we find small and non-significant results.

Table B.1—Estimated Price Effects of the Macron Law: Anticipation and Delays

	Outcome: Log Price × 100			
	1 MONTH		2 MONTHS	
	WEB (1)	OTA (2)	WEB (1)	OTA (2)
Panel A. Anticipation Effects				
τ^{TWFE}	−0.983	−0.225	−0.675	0.381
	(1.873)	(2.374)	(1.889)	(2.151)
Room Nights (ρ)	0.004	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,222	5,209	5,222	5,209
Panel B. Delayed Effects				
τ^{TWFE}	−1.392	−2.202	−1.299	−2.958
	(2.213)	(2.334)	(2.258)	(2.545)
Room Nights (ρ)	0.004	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,222	5,209	5,222	5,209

Note: This table reports the estimations of the anticipated and delayed effects of prohibiting PPCs on hotel room prices. The WEB and OTA column headers report coefficients estimated using subsets of data from the WEB and OTA channels, respectively. Panel A reports the anticipation effects, and Panel B reports the delayed effects. The dependent variable is the logarithm of monthly average channel price × 100. Room Nights (ρ) indicates estimated coefficients of the monthly room nights sales variable. Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotel fixed effects. The coefficients are estimated using Equation (1). Robust standard errors are clustered at the city level and reported in parentheses.

C Placebo Test – Random Treatment Assignment

In this Appendix, we perform a placebo test on our benchmark specification by randomly assigning treatment status to hotels in any country. This analysis is similar to those performed in the SCM literature (Abadie, 2021). We show that our non-significant point estimates could have reasonably resulted from a random sample. Figures C.1 and C.2 present the distribution of the estimated placebo treatment effects for WEB and OTA, respectively.

The distributions are generated by estimating 1000 times our benchmark TWFE DID specifications in Table 2, Panel A, Columns (3) and (4), but randomly assigning the treatment status. In each iteration, the treated status is randomly assigned to any hotel, but we maintain the total share of treated units as in our main specifications. The actual estimated coefficients (vertical red lines) lie within the distribution of the randomly-assigned placebo estimates.

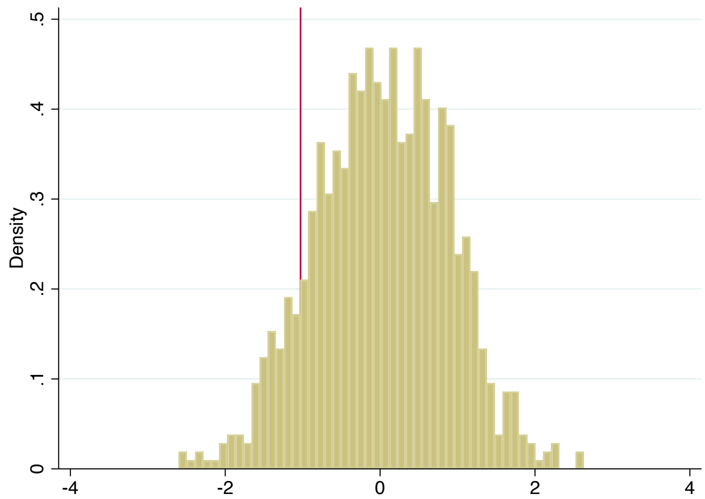


Figure C.1: Distribution of the Estimated Placebo Treatment Effects for WEB. Vertical red line: actual estimate from Table 2, Panel A, Column (3).

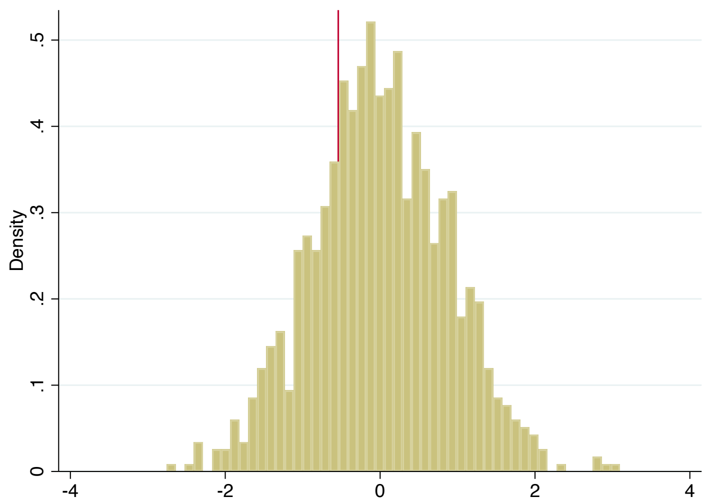


Figure C.2: Distribution of the Estimated Placebo Treatment Effects for OTA. Vertical red line: actual estimate from Table 2, Panel A, Column (4).

D Heterogeneous Treatment Effects

Table D.1—Estimated Price Effects of the Macron Law: Heterogeneity In Star Ratings

	Outcome: Log Price $\times$ 100					
	3 STARS		4 STARS		5 STARS	
	WEB	OTA	WEB	OTA	WEB	OTA
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. France vs Control						
τ^{TWFE}	0.065	-2.250	-0.088	-0.319	-5.140	-0.429
	(3.411)	(2.804)	(2.354)	(3.268)	(3.429)	(3.983)
Room Nights (ρ)	0.010	0.009	0.004	0.003	0.005	0.006
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Months FE	✓	✓	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓	✓	✓
No. of Hotels	35	35	92	92	26	26
Observations	1,237	1,231	3,108	3,103	877	875

Note: This table reports the estimated heterogeneous price effects of prohibiting PPCs on chain hotels of different star ratings. The WEB and OTA column headers report coefficients estimated using subsets of data from the WEB and OTA channels, respectively. The dependent variable is the logarithm of monthly average channel price $\times$ 100. Room Nights (ρ) indicates estimated coefficients of the monthly room nights sales covariate. Months FE (γ_t) indicates time fixed effects. Hotels FE (δ_i) denotes the hotel fixed effects. Robust standard errors are clustered at the city level and reported in parentheses.

Table D.2—Estimated Price Effects of the Macron Law: Heterogeneity In Hotel Sizes

	Outcome: Log Price $\times$ 100					
	SMALL (< 150 Rooms)		MEDIUM (150-300 Rooms)		LARGE (> 300 Rooms)	
	WEB	OTA	WEB	OTA	WEB	OTA
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. France vs Control						
τ^{TWFE}	0.089	-0.553	1.195	1.667	-11.21	1.287
	(2.788)	(2.698)	(2.488)	(3.158)	(1.991)	(3.028)
Room Nights (ρ)	0.007	0.007	0.006	0.006	0.004	0.004
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Months FE	✓	✓	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓	✓	✓
No. of Hotels	69	69	62	62	22	22
Observations	2,357	2,349	2,106	2,101	759	759

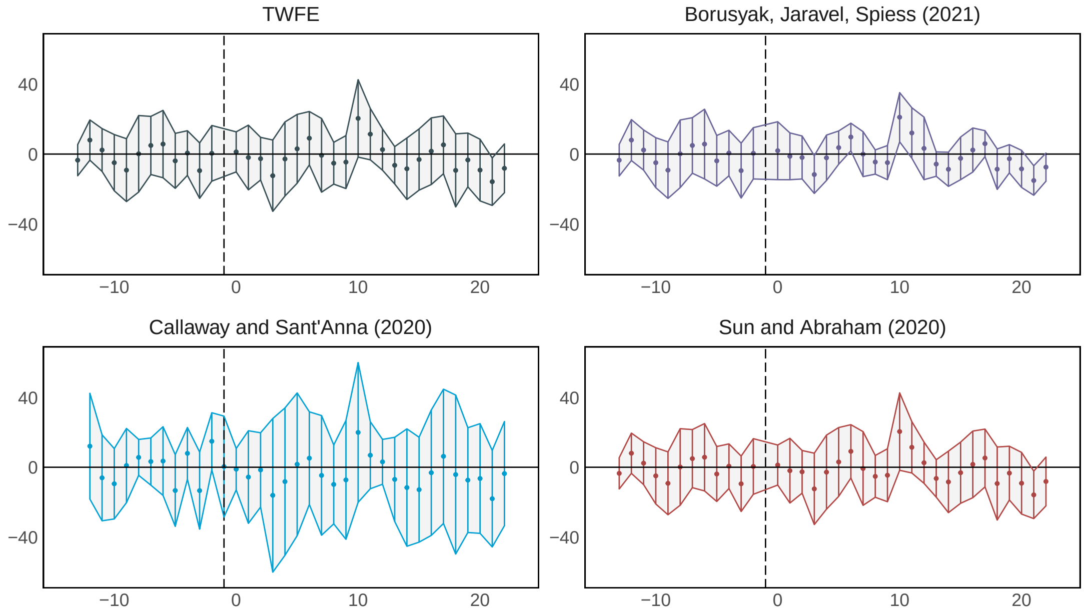
Note: This table reports the estimated heterogeneous price effects of prohibiting PPCs on chain hotels of different sizes. The WEB and OTA column headers report coefficients estimated using subsets of data from the WEB and OTA channels, respectively. The dependent variable is the logarithm of monthly average room price $\times$ 100. Room Nights (ρ) indicates estimated coefficients of the monthly room nights sales covariate. Months FE (γ_t) indicates time fixed effects. Hotels FE (δ_i) denotes the hotel fixed effects. Robust standard errors are clustered at the city level and reported in parentheses.

E Alternative DID Estimators

We use the R package `did2s` developed by Butts and Gardner (2021) to implement event study analyses using several newly-developed DID estimators. Similar to the results of TWFE DID, we obtain non-significant results on both the WEB and OTA channels. This holds both for the Macron Law (Section E.1) and when we consider the policy changes in France, Germany, and Austria as a series of staggered treatments (Section E.2).

E.1 The Macron Law

Panel A. Event Study: WEB Channel



Panel B. Event Study: OTA Channel

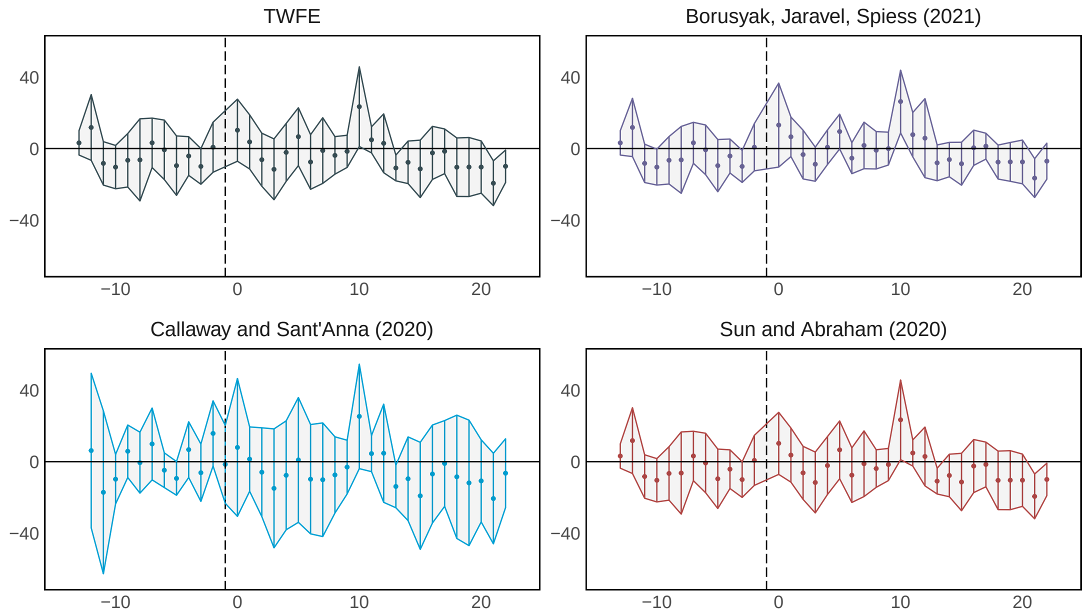
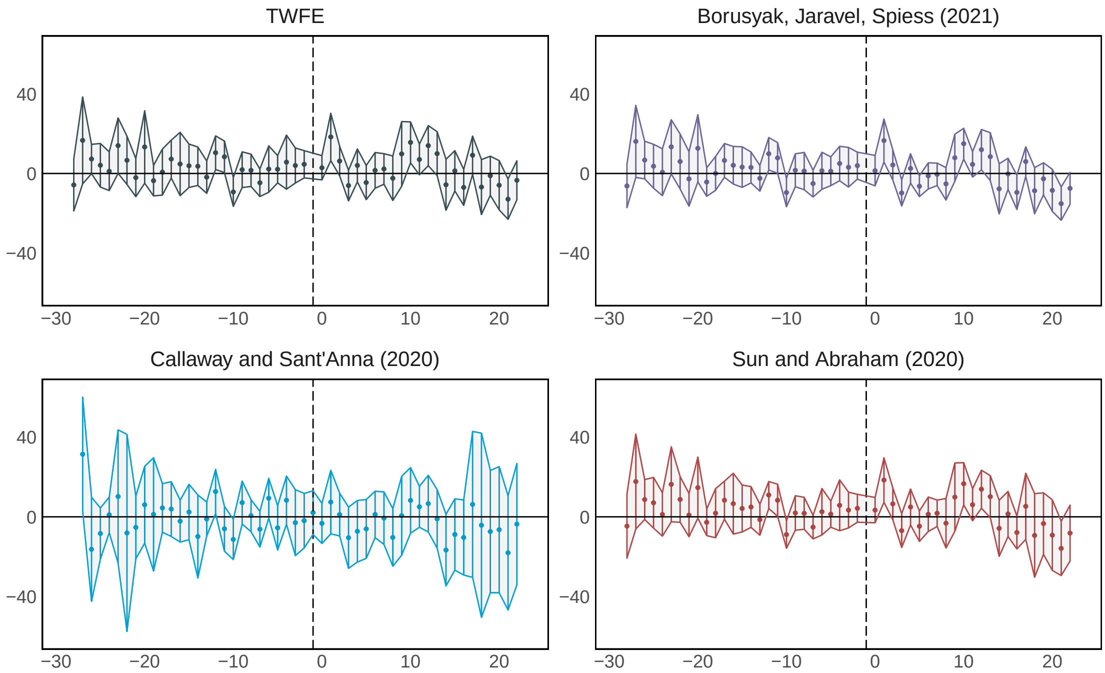


Figure E.1: Event Study of the Macron Law — Alternative Estimators

E.2 External Validity

Panel A. Event Study: WEB Channel



Panel B. Event Study: OTA Channel

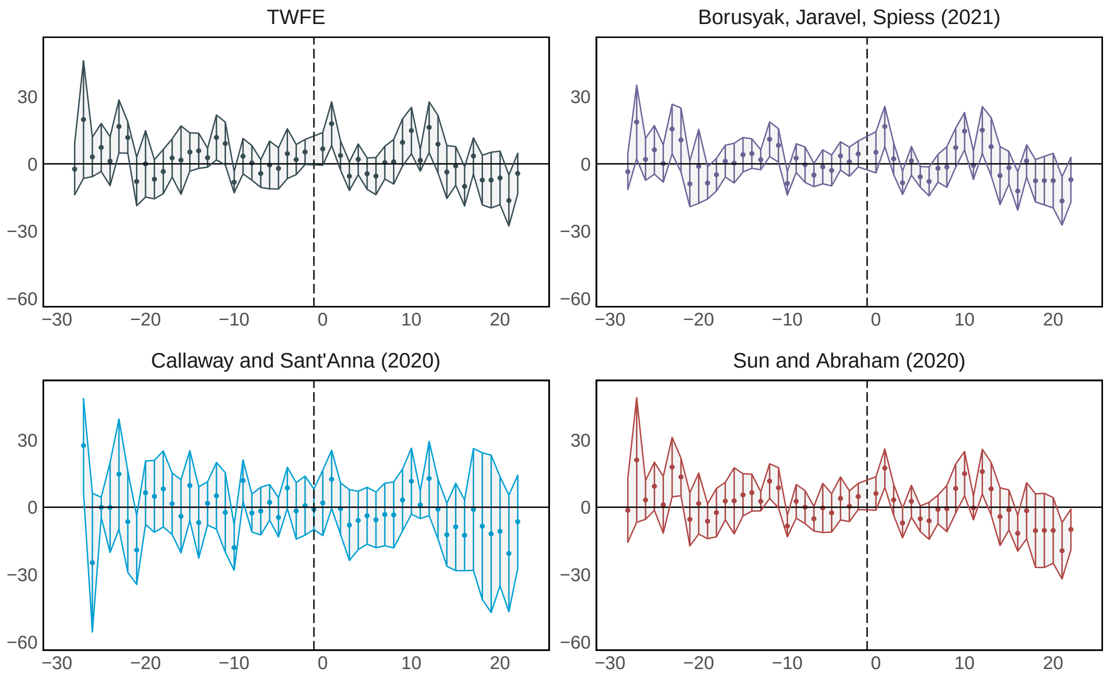


Figure E.2: Event Study of Prohibiting PPCs — Alternative Estimators

F Offline Distribution Channels

In this Appendix, we evaluate the *hypothetical* price effects of the Macron Law on offline channels. Indeed, the current literature does not provide clear theoretical guidance about how the removal of OTAs' PPCs would affect these sales channels. The only partial exception is the paper by Bisceglia, Padilla and Piccolo (2021), which, however, focuses on wholesale parity agreements, a related but different practice.

Table F.1—Estimated Price Effects of the Macron Law: Offline Channels

	Outcome: Log Price × 100			
	GDS (1)	INN (2)	WHO (3)	OTH (4)
Panel A. France vs Control				
τ^{TWFE}	−1.048	−3.174	−13.30	1.281
	(1.870)	(2.226)	(3.103)	(3.441)
Room Nights (ρ)	0.004	0.005	0.006	0.002
	(0.001)	(0.001)	(0.002)	(0.001)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,099	9,948	1,091	1,498
Panel B. Germany vs Control				
τ^{TWFE}	2.965	2.465	−13.31	−0.760
	(2.714)	(3.005)	(3.817)	(5.976)
Room Nights (ρ)	0.003	0.004	0.005	0.003
	(0.001)	(0.001)	(0.002)	(0.001)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	5,606	10,930	993	1,843
Panel C. Austria vs Control				
τ^{TWFE}	1.026	0.246	−12.86	3.986
	(1.982)	(2.911)	(6.841)	(2.778)
Room Nights (ρ)	0.004	0.005	0.005	0.002
	(0.001)	(0.001)	(0.002)	(0.001)
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓
Observations	4,997	9,708	952	1,503

Note: This table reports the estimated price effects of prohibiting PPCs on the offline distribution channels using TWFE. Columns (1) to (4) report the estimated price effects on the GDS, INN, WHOLESALE, and OTHER channels, respectively. Panels A, B, and C report the price effects on these channels by comparing hotels in France, Germany, and Austria to those in the control group, respectively. The dependent variable is the logarithm of monthly average room price × 100. Room Nights (ρ) indicates estimated coefficients of the monthly room nights sales variable. Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotel fixed effects.

Furthermore, we are unsure whether PPCs were *de facto* applied to these channels or not, as it is hard for OTAs to monitor the sellers' pricing behavior. Moreover, these channels are either offline or directed towards businesses (or both), which makes it difficult to observe the relevant shocks affecting them during the period of our study. Regardless, none of the channels exhibits a significant price reduction, except for Wholesale, which nonetheless accounts for only 1.7% of the total transactions.

G Synthetic Difference-in-Differences

Table G.1, which is a more complete version of Panel B of Table 2, reports the SDID estimates of the Macron Law. It also contains the country and month weights used to create the pre-treatment parallel trends of the synthetic control. Overall, we find that the country weights are relatively balanced for the WEB synthetic control. This insight confirms the validity of our DID methodology, which assigned equal weights to all control countries. However, country weights for the OTA synthetic control are more unbalanced.

Table G.1—Estimated Price Effects of the Macron Law: SDID Results

	Outcome: Log Price $\times$ 100	
	WEB (1)	OTA (2)
Panel A. SDID Results		
τ^{SDID}	-0.747	-0.806
	(3.750)	(2.795)
Room Nights (ρ)	0.010	0.011
	(0.003)	(0.003)
Belgium	0.145	0.137
Italy	0.168	0.146
Netherlands	0.145	0.134
Portugal	0.181	0.232
Spain	0.183	0.183
United Kingdom	0.178	0.168
Month 2	0.000	0.167
Month 7	0.392	0.438
Month 9	0.181	0.000
Month 10	0.000	0.147
Month 11	0.000	0.184
Month 12	0.338	0.000
Observations	252	252

Note: This table reports the SDID results estimated using Equation (3). The two column headers report coefficients estimated using subsets of data from the WEB and OTA channels, respectively. SDID standard errors are reported in parentheses. The row headers of country names report the optimised unit weight assigned to each country. The row headers of month numbers report the optimised time weights assigned to each cumulative month before the Macron Law. Only the months with non-zero weights are reported. The dependent variable is the logarithm of monthly average channel price $\times$ 100. Room Nights (ρ_{it}) indicates the room nights control.

H External Validity — Individual Results from Matrix Completion

Table H.1—Estimated Price Effects of Prohibiting PPCs: MC-NN Results

	Dependent Variable: Log Price × 100			
	Excluding Paris		Including Paris	
	WEB	OTA	WEB	OTA
	(1)	(2)	(3)	(4)
France vs Control	−1.018	−0.540	−2.608	−3.206
	(1.999)	(2.383)	(2.149)	(2.787)
Germany vs Control	2.847	1.255	2.847	1.255
	(3.037)	(3.039)	(3.037)	(3.039)
Austria vs Control	1.808	1.534	1.808	1.534
	(3.866)	(3.644)	(3.866)	(3.644)
Room Nights (ρ)	✓	✓	✓	✓
Months FE	✓	✓	✓	✓
Hotels FE	✓	✓	✓	✓

Note: This table reports the external validity of our results using non-parametric MC-NNM from Equation (4). The WEB and OTA column headers report coefficients estimated using subsets of data from the WEB and OTA channels, respectively. For robustness, we report the results of both excluding and including Paris in the treatment group. Room Nights (ρ) indicates estimated coefficients of the monthly room nights sales variable. Months FE (γ_t) indicates the cumulative months fixed effects. Hotels FE (δ_i) denotes the hotel fixed effects.

I Anecdotal Evidence of PPCs and Their Monitoring

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

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

Booking.com

Gentile Partner,

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

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

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

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

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

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

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

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

Booking.com

Dear

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

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

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

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

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

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

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

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

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

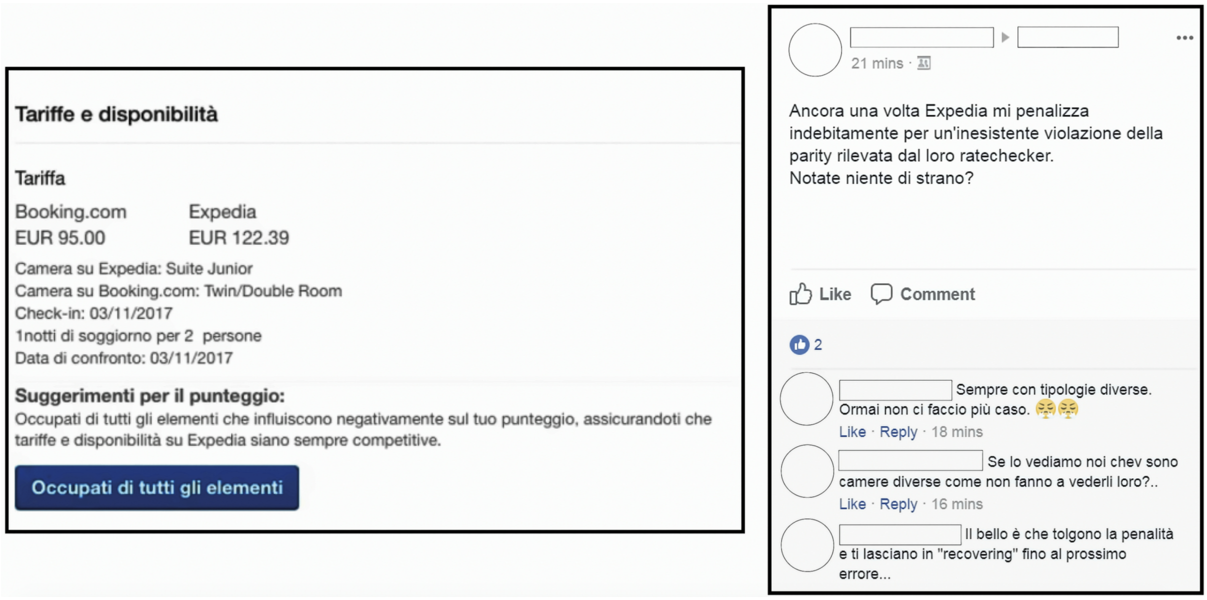


Figure I.3: The Monitoring of PPCs: Evidence from a Facebook Forum of Italian Hoteliers