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Abstract

This paper investigates the impact of price transparency on equilibrium prices and fees by considering a policy change implemented by Airbnb that affected the transparency of cleaning fees for IP addresses from the European Union (EU). Using a difference-in-differences approach, we find a reduction in cleaning fees of 2-4%. Consistent with our theoretical framework, we also find that listings without a cleaning fee, something that is common on Airbnb, appear more affordable after the policy change and react by increasing their nightly price by 5-6%. We argue that this result is driven by some hosts learning about the full prices of their rivals due to the transparency policy, finding themselves more affordable. This analysis uncovers a new mechanism through which greater price transparency can lead to price increases.

JEL-Codes: D400, D800, L100, L200, L400.

Keywords: price transparency, obfuscation, cleaning fees.

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1 Introduction

The presence of shrouded prices and hidden fees is a widespread issue on many online platforms. On ticket resale platforms such as StubHub or Ticketmaster, consumers are often enticed by initially attractive ticket prices, only to find additional fees for processing and service charges added at the final checkout stage.[1] Similarly, food delivery services like Grubhub and DoorDash frequently advertise low delivery costs, but later add additional fees for service, delivery, and small orders. In the hospitality industry, platforms like Airbnb and VRBO have historically advertised competitive base prices, with additional charges, such as cleaning and service fees, only disclosed after the listing has been selected.

Shrouded fees increase the complexity of consumer decision-making by imposing additional search costs (Ellison and Ellison, 2009). Because consumers must devote more time and effort to uncover the full costs of each option (Gabaix and Laibson, 2006), the presence of shrouded fees can lead to suboptimal choices (Brown et al., 2010; Chiles, 2021). Some users may opt for what appears to be a cheaper option based on incomplete information, only to face final prices higher than expected once all fees are revealed (Chetty et al., 2009; Taubinsky and Rees-Jones, 2018). Due to these challenges, several governments and regulatory bodies are considering or have already implemented measures to regulate or ban such practices. For instance, the US government has pushed for a crackdown on so-called "junk fees"; whereas the UK has proposed new laws aimed at banning mandatory hidden fees in online shopping.[2]

Previous studies have primarily focused on the demand-side response to shrouded fees, especially in contexts where prices do not adjust with changes in transparency (for example, Blake et al., 2021). This paper expands the focus to include the supply-side response to mandated price transparency, which is especially important in peer-to-peer markets where some suppliers, like consumers, may not behave fully rationally. We examine the online short-term rental platform Airbnb, where hosts set nightly prices as well as cleaning fees. A distinctive feature of peer-to-peer marketplaces like Airbnb is that obscured fees not only affect consumers but also hinder other hosts from easily comparing competitors' total prices. As a result, hosts face search costs to learn about competitors' prices, which plays a crucial role in understanding how price transparency impacts market outcomes.

To investigate this, we leverage a policy change that affects Airbnb's platform design in Europe, stemming from negotiations between Airbnb and the European Commission that began in July 2018. Prior to

[1] For more information, see: https://www.theverge.com/2023/10/26/23933230/live-nation-ticketmaster-hidden-junk-fees-venue (last accessed: December 4, 2024).

[2] See https://www.forbes.com/sites/willskipworth/2023/10/11/biden-wants-to-ban-junk-fees---the-hidden-costs-tacked-onto-concert-tickets-hospital-bills-and-more/ and https://www.gov.uk/government/news/new-laws-set-to-ban-mandatory-hidden-fees-from-online-shopping-saving-money-for-consumers (both last accessed: December 4, 2024).

these negotiations, service and cleaning fees on Airbnb were only revealed at later stages of the booking process. Following these negotiations, Airbnb made these fees fully transparent, but only to users based in the European Union (EU). Specifically, in September 2018, Airbnb committed to fully showing these fees along with the per-night prices for EU-based users when they searched for accommodations from January 2019. However, this level of transparency was not extended to guests booking from non-EU countries, who continued to encounter fees only at later stages of the booking process.

We use listing-level data from London, the city with the highest number of Airbnb listings in Europe and subject to EU laws and regulations for the period of our analysis. To assess how price transparency affects asked cleaning fees, we apply a difference-in-differences (DiD) design in which we assign the treatment status based on the proportion of past EU guests in the listing's vicinity. Because Airbnb introduces price transparency only for EU-based users, listings with a larger exposure to guests from the EU are more likely affected. Consequently, we define the treatment group as listings with an above-city-median exposure to EU guests. If guests are at least partially inattentive to hidden fees, these listings' hosts have stronger incentives to reduce cleaning fees once price transparency is implemented, because guests become attentive to the full price and these listings would be perceived as less affordable compared to other listings. In contrast, hosts who can expect more non-EU guests face less pressure to adjust their fees, as many of their guests continue to see the shrouded pricing structure. Our analysis reveals that listings with an above-median proportion of EU guests reduce their cleaning fees by approximately 0.7 GBP, or 2%, in response to price transparency, compared to hosts with a below-median proportion of EU guests.[3] Furthermore, event study analyses confirm that the reduction began around September 2018 and became more pronounced beginning January 2019, when the new design of the platform was fully implemented.

The limited reduction in cleaning fees suggests that Airbnb hosts primarily used these fees for purposes other than deceiving inattentive guests. Instead, cleaning fees may serve practical purposes, such as covering actual cleaning costs or encouraging longer stays by making short stays relatively more expensive.[4] In particular, nearly 27% of Airbnb listings never charge a cleaning fee in London, which is consistent with an Airbnb statement in 2021 that 45% of listings worldwide did not charge a cleaning fee.[5] Further analysis shows that the change in price transparency also affected hosts who do not use cleaning fees at all. Some Airbnb hosts may face similar attention and search constraints as consumers do, thus being affected by obfuscated prices. When prices are not fully transparent, these hosts may struggle to accurately compare

[3] The effect is similar for both asked cleaning fees, fees set by hosts regardless of whether the stay is booked, and booked cleaning fees, fees charged for stays that are actually booked by guests.

[4] For more information, see: https://www.airbnb.com/resources/hosting-homes/a/how-to-set-a-cleaning-fee-470 (last accessed: December 4, 2024).

[5] See: https://news.airbnb.com/fee-transparency-on-airbnb/ (last accessed: December 4, 2024).

their prices with those of competitors. In some cases, hosts with lower or no cleaning fees may appear more expensive while the fees are hidden, even if their total price is actually lower than the competitors' with high cleaning fees. The policy change also reduces the search costs for hosts, allowing them to more easily observe the full prices of competitors and adjust their pricing strategies accordingly.

To study this pricing mechanism, we measure how each listing's perceived affordability compared to similar listings changes due to the move from shrouded fees to unshrouded fees. Specifically, we compare the per-night prices (excluding the cleaning fee) of each listing in the year before the policy change with the per-night prices of similar nearby listings. Then, we perform the same analysis using the total price, including both the per-night rate and cleaning fees. By comparing these two prices, we study how price transparency affected each listing in terms of its relative affordability. Listings that charged zero or very low cleaning fees were likely to appear more affordable after the policy change, while those that kept low per-night prices but charged high cleaning fees are more likely to see a decline in perceived affordability. Indeed, we find that hosts whose listings appear more affordable with transparent fees increase their prices after the policy change compared to other listings. This result confirms the idea that price transparency can impact both the buyer and seller sides of peer-to-peer markets.

We conclude our analysis by comparing the evolution of per-night prices and cleaning fees in London and New York City. Our findings reveal that asked cleaning fees decreased in London compared to New York City following the policy change. Furthermore, we find that listings that are perceived to become more affordable with price transparency, increase their per-night price in London compared to those in New York City. The same does not happen for listings that become relatively more expensive with price transparency. Overall, these results are in line with what we find in the analysis focusing exclusively on London.

We assess the overall impact of the policy by examining how booked prices and quantities were affected. We find that listings that were more affordable before the policy not only increased their prices but also received fewer bookings and shorter lengths of stay after the policy, which ultimately reduced their post-policy revenues. We also extend our analysis in several ways. First, we examine how more professional hosts respond to the policy, who are more likely to be more responsive than others to the price transparency. Using Superhost status, a badge system assigned by Airbnb to reliable hosts with a high occupancy rate and low cancellation rates, as a proxy for professionalism, we find that greater exposure to EU travelers makes Superhosts more responsive to the policy compared to non-Superhosts (e.g., 1 GBP). Second, we find that hosts did not use the cleaning fee to screen consumers based on their desired length of stay, since the minimum number of nights decided by hosts did not change as a result of the policy.

Our article contributes to the literature on price obfuscation and its implications for markets and consumer welfare. Previous research has mainly focused on demand-side reactions to price obfuscation. In many settings, consumers seem to partially ignore the additional fees. This behavior has been documented with respect to auction fees in lab experiments (Morwitz et al., 1998), field experiments (Hossain and Morgan, 2006; Brown et al., 2010) as well as observational data (Einav et al., 2015). Blake et al. (2021) also document this effect for platform fees in posted prices using a field experiment on StubHub, a ticket resale platform. However, Dertwinkel-Kalt et al. (2020) show that this inattention to fees may not always be present and propose that it may depend on the cost of canceling the search once the full price is revealed. These results suggest that, overall, it is beneficial for sellers to obfuscate part of the price. In the context of peer-to-peer platforms, we show that this may not necessarily be the case, as obfuscation generates frictions (e.g., inattention, search costs) that lead some sellers to set prices "too" low. By removing these frictions, price transparency benefits these sellers.[6]

Relatedly, Ellison and Ellison (2009) show how computer memory chip retailers use low prices on online price comparison sites to attract customers, only to steer them toward higher-margin products once they reach the site. Our paper contributes to this literature by showing how sellers adjust their pricing strategies when transparency is mandated. As such, our results also relate to the literature analyzing the impact of mandated price transparency in the gasoline market (Luco, 2019; Martin, 2024). While previous work suggests that prices might decrease as a result of increased transparency (Ellison and Ellison, 2018), our results show that other forces may induce sellers to raise prices, especially in an online platform context with many non-professional sellers. Notably, this is due to the intrinsic characteristics of a peer-to-peer platform, and that shrouded fees can make prices obfuscated on both sides of the market. While consumers may still benefit from transparency due to reduced search costs and preference for the fairness associated with transparent pricing (Seim et al., 2017; Mamadehussene, 2020; Allender et al., 2021), the increase in total prices could partially offset these positive effects on consumer welfare. Several studies have compared the pricing behavior of non-professional hosts in Airbnb, who may struggle to adjust prices flexibly, with the platform's "smart pricing" algorithm (Ye et al., 2018; Pan and Wang, 2021; Huang, 2022; Foroughifar, 2023). We use the Superhost status as a proxy for professional hosts and find that they react more strongly to the price transparency change when exposed to above-median EU travelers. We also observe that a subset of hosts changes prices very frequently, which may indicate the adoption of pricing algorithms. In our context, the presence of such hosts might have mitigated the price response to the policy change, as any reaction

[6] We also contribute to the literature on decentralized versus centralized pricing strategies on online platforms (Allon et al., 2012; Aouad et al., 2023). Pricing decisions could be decentralized, as seen on platforms like Airbnb or Amazon, where individual sellers set prices, or centralized, as with Uber, where the platform controls pricing (Castillo et al., 2017). Platforms typically have better access to data and can implement more efficient pricing strategies. However, their goals may not fully align with the profit maximization of individual sellers (Filippas et al., 2023).

would likely be short-lived. More directly related to fee obfuscation, Johnen and Somogyi (2024) explore the different incentives for shrouding fees between platforms and individual sellers. In our study, we show that Airbnb's lack of transparency in cleaning fees may have encouraged only a minority of hosts to use the fees "deceptively", but this was enough for some hosts to adjust their prices and cleaning fees.

The paper proceeds as follows. In Section 2, we provide background on Airbnb's negotiations with the European Commission in 2018, describe our dataset, and explore hosts' pricing strategies. Section 3 outlines the theoretical framework that informs our empirical approach. In Section 4, we examine the impact of transparency on hosts' cleaning fees, while Section 5 analyzes the effects on per-night prices. Section 6 presents the same analyses using an alternative identification strategy. Section 7 presents the overall policy impact. Section 8 presents further results. Finally, Section 9 offers concluding remarks and discusses the policy implications of our findings.

2 Empirical Setting and Dataset

2.1 Airbnb and its Discussions with the European Commission

Airbnb is a peer-to-peer platform connecting hosts with guests seeking short-term stays. Hosts can list their properties, which range from shared rooms to entire homes, and are responsible for setting the nightly rate, additional fees (e.g., cleaning fees), and terms such as house rules and minimum stay requirements. The cleaning fee is a one-time charge applied per stay, regardless of the length of the reservation.[7] Hosts also manage their property's availability and can adjust prices based on demand or seasonality. Guests browse the listings, compare options, and make reservations by selecting the available dates and paying the total price, which includes the nightly rate, service fees, and any other applicable charges.

Before 2018, Airbnb's pricing practices around the world, including in the EU, lacked transparency around mandatory additional charges such as cleaning fees, service fees, and local taxes. Search results would saliently display the price per night excluding any fees. Additional fees would only be clearly revealed later in the booking process. In July 2018, the European Commission, along with the Norwegian Consumer Authority, demanded that Airbnb revise its pricing practices to comply with EU consumer protection laws. European authorities gave Airbnb until the end of August 2018 to propose a solution, warning that enforcement action would be taken if satisfactory changes were not implemented.[8]

By September 2018, Airbnb had agreed to comply with these requests. The company committed to

[7] For more information, see: `https://www.airbnb.com/help/article/2812` (last accessed: December 12, 2024).

[8] For the official EU declaration, see: `https://ec.europa.eu/commission/presscorner/detail/en/IP_18_4453` (last accessed: December 12, 2024).

(a) EU IP Address **(b)** US IP Address

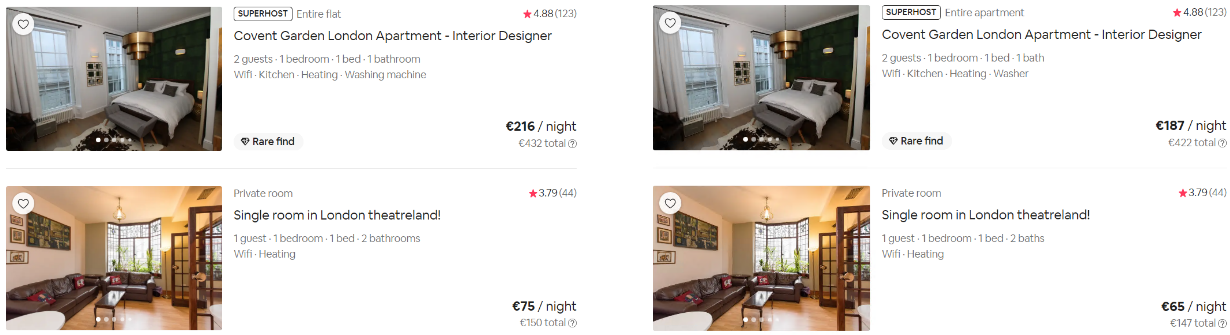


Figure 1. Airbnb search results in London as viewed by EU versus US IP addresses in February 2020.

displaying the total, all-inclusive price per night (including cleaning and service fees) on all EU versions of its platform by the end of 2018.[9] Accordingly, as of January 2019, consumers in the EU searching for accommodations on Airbnb would immediately see the full price of their booking, including any applicable service fees, cleaning fees, and local taxes upfront, ensuring a more transparent user experience. By July 2019, the European Commission confirmed that Airbnb was fully compliant with EU consumer protection standards and that the platform had been successfully redesigned to ensure price transparency in all EU countries.[10] However, the changes implemented in the EU were not mirrored in other markets. In the US, for example, Airbnb continued its previous practice of revealing additional fees only in the later stages of the booking process. To illustrate these differences, Figure 1 compares two Airbnb listings in London as viewed in the search results by users with EU-based IP addresses (left panel) and US-based IP addresses in 2020 (right panel). Only in 2022 did Airbnb commit to implement a global shift toward price transparency.[11]

2.2 Data and Descriptives

For our analysis, we require information on Airbnb listings' prices, cleaning fees, and exposure to travelers from the EU. For this purpose, we combine three main data sources. The first source is web-scraped data on Airbnb demand and supply provided by AirDNA.[12] These data include daily information on the price of each listing, whether a listing was available for booking, and whether it was booked. If a listing was booked,

[9] For the official EU declaration, see: https://ec.europa.eu/commission/presscorner/detail/en/ip_18_5809 (last accessed: December 12, 2024).

[10] For the official declaration, see: https://ec.europa.eu/commission/presscorner/detail/en/IP_19_3990 (last accessed: December 12, 2024).

[11] See the official tweet by Brian Chesky, CEO of Airbnb: https://x.com/bchesky/status/1589541705921212416 (last accessed: December 12, 2024).

[12] AirDNA is a data analytics provider that compiles and analyzes short-term rental data, primarily from Airbnb. For more information, see: https://www.airdna.co/.

Table 1. Descriptive statistics

	Obs.	Mean	SD
Nightly price	1,030,459	154.82	244.86
Cleaning fee	1,030,459	33.53	41.14
Cleaning fee > 0	1,030,459	0.73	0.44
Entire home	1,030,459	0.57	0.50

the dataset also includes the time of booking. The second dataset contains Airbnb review data, also sourced from AirDNA. These data contain all text reviews that a listing has received, along with some information about the guests who left the reviews. Importantly for our analysis, the data include the self-reported home location for most guests. AirDNA does not provide time-varying information on cleaning fees. Thus, we supplement the dataset with monthly snapshots from InsideAirbnb, which is our third dataset.[13] These monthly datasets report the cleaning fee for the majority of listings.

To combine these data sets, we aggregate the daily AirDNA data to months. Then, we merge the monthly InsideAirbnb data to match the monthly cleaning fee information to the AirDNA data. This matching requires us to make certain assumptions. Most importantly, for many listings, cleaning fees are always missing in the InsideAirbnb data. For these cases, we assume that the listings have not set a cleaning fee, i.e. the fee is zero. In Appendix A, we describe in more detail the data matching procedure and how we handle missing information on cleaning fees.

We restrict the analysis to data from January 2018 to December 2019 and to those listings which we observe at least twice during that period. We focus on London, the city with the highest number of Airbnb listings in Europe and subject to EU laws for the period of our analysis.[14] We restrict the analysis to private rooms and entire homes that represent the vast majority of our data. Furthermore, we only include listings in months in which they were available for at least one day.

Table 1 provides descriptive statistics for our sample. Listing prices in London are approximately 155 GBP per night, but there is a large dispersion. The average cleaning fee is about 33 GBP, again with a large dispersion. Most listings are entire homes (57%) rather than private rooms. Moreover, a large share of observations, 27%, have a cleaning fee of zero. Interestingly, each listing either always has a cleaning

[13] InsideAirbnb is an independent project that collects and shares data about Airbnb listings. For more information, see: `https://insideairbnb.com/`.

[14] The UK formally left the EU on January 2020. However, the UK remained in a transition period where it continued to follow EU rules and regulations until December 2020. However, the UK maintained the same transparency policy with respect to Airbnb fees after 2020. In Appendix F we also consider the next two largest European cities in terms of Airbnb listings, Paris and Rome. Each of these cities has their own issues for this analysis, which we discuss in the Appendix as well, and which is why we include the results more as a robustness exercise.

fee of zero or always has a positive fee; there are very few listings that switch between a zero fee and a positive fee or vice versa. This pattern can be seen in Panel (a) of Figure 2. Each observation underlying this histogram is one Airbnb listing. For each listing, we calculate the share of observations for which we observe a positive cleaning fee. The histogram shows the distribution of the share of observations with a positive fee over all listings in the sample. The figure reveals a bimodal distribution in which almost all listings either never have a fee larger than zero or always do. Panel (b) of Figure 2 displays the share of listings that never charge a cleaning fee by Lower Super Output Areas (LSOA). The map shows substantial heterogeneity within the city. Specifically, areas in the city center tend to have a lower share of zero-fee listings, indicating that central listings are more likely to charge a cleaning fee.

(a) Share of observations with positive fee by listing

(b) Share of listings without cleaning fees by LSOA

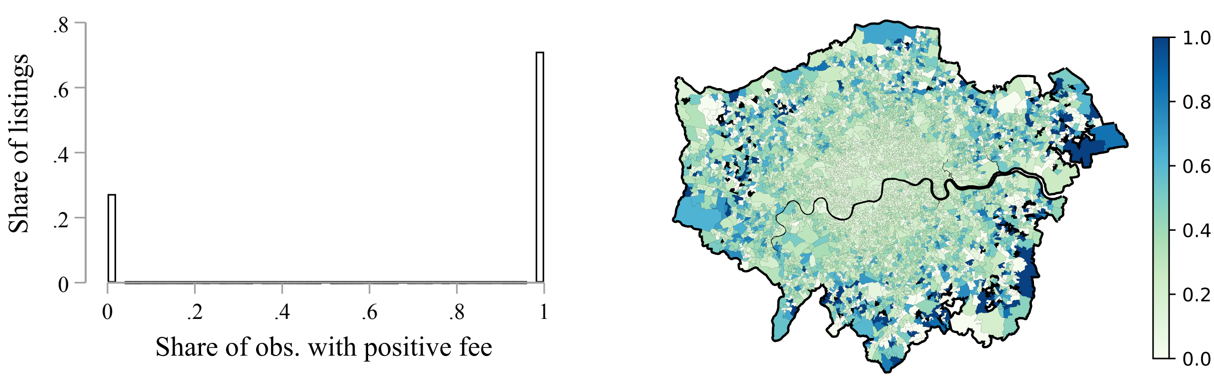


Figure 2. Distribution of listings with and without cleaning fees

3 A Simple Model with Two Types of Hosts

To provide some insights on possible mechanisms at play when price transparency changes, we provide a stylized model with two types of hosts: hosts that utilize the cleaning fee and are aware of cleaning fee shrouding (Host 1) and hosts that only utilize the listing price and are unaware of cleaning fees as long as they are shrouded (Host 2).[15] This modeling is in line with the evidence that some hosts never set a cleaning fee (see Panel (a) in Figure 2). The two hosts are price setters and are differentiated competitors so that

[15]One way to rationalize this heterogeneity is that the second set of hosts faces sufficiently high search costs (or time-constrains), preventing them from discovering whether rivals have a strictly positive cleaning fee. Generally, prior research has found evidence that hosts on Airbnb do not necessarily act as perfect profit maximizers (see, e.g. Huang, 2022; Li et al., 2022).

demands are given by:

$$Q_1 = \sum_{n=1}^{N}\left[\left(a - bP_1 - b\frac{f}{n}\lambda + dP_2\right) n\cdot M(n)\right],$$
$$Q_2 = \sum_{n=1}^{N}\left[\left(a - bP_2 + dP_1 + Sd\frac{f}{n}\right) n\cdot M(n)\right],$$

where P_i is the nightly listing price, f is Host 1's cleaning fee, n is the number of nights, $M(n) \in [0,1]$ is the mass of consumers interested in n nights so that $\sum_{n=1}^{N} M(n) = 1$, $\lambda \in [0,1]$ is the degree of obfuscation of the cleaning fee (i.e., $\lambda = 1$ implies no obfuscation), $d < b$ captures the strength of price competition between hosts, and $S \in \{0,1\}$ captures the policy shock that makes Host 2 aware of Host 1's cleaning fee. For simplicity, we assume that costs are zero (this does not affect the main results).

Defining host profits, we note that Host 2 is unaware of cleaning fees pre-policy and fully accounts for them post-policy. Hence, λ does not impact their price setting behavior and we see that in how each host defines its profit used in price setting:

$$\Pi_1 = \sum_{n=1}^{N}\left[\left(a - bP_1 - b\frac{f}{n}\lambda + dP_2\right)\left(P_1 + \frac{f}{n}\right) n\cdot M(n)\right],$$
$$\Pi_2 = \sum_{n=1}^{N}\left[\left(a - bP_2 + dP_1 + Sd\frac{f}{n}\right)(P_2) n\cdot M(n)\right] = [\overline{n}(a - bP_2 + dP_1) + Sdf]\, P_2,$$

where $\overline{n} = \sum_{n=1}^{N} n\cdot M(n)$. From the first-order conditions of the hosts' profit with respect to prices and fees, we obtain the following result.[16]

Lemma 1. *In equilibrium, the P_1, f, and P_2 best-response functions are given by:*

$$P_1 = \frac{1}{2b}(a + dP_2) - \frac{1+\lambda}{2}\cdot\frac{f}{\overline{n}},$$
$$f = \frac{1}{\overline{\eta}}\left[\frac{1}{2b\lambda}(a + dP_2) - \frac{1+\lambda}{2\lambda}\cdot P_1\right],$$
$$P_2 = \frac{1}{2b}\left(a + dP_1 + Sd\frac{f}{\overline{n}}\right),$$

where $\overline{\eta} = \sum_{n=1}^{N} \frac{1}{n} M(n)$.

All proofs are in Appendix B.

These best-response functions allow us to isolate two important effects that we shall consider empirically. First, we identify how price transparency *directly* impacts Host 1's listing price and cleaning fee

[16] The second-order conditions for Host 2 always hold; for Host 1, second-order conditions require $4\lambda\overline{\eta}\frac{1}{\overline{n}} > (1+\lambda)^2$, which we assume throughout the analysis.

when competitive effects are ignored (i.e., $d = 0$). This gives us a direct comparison with the existing literature on obfuscation. Second, we identify how price transparency *indirectly* impacts Host 1's listing price and cleaning fee via a change in Host 2's listing price. We consider each of these effects in the following propositions.

Consistent with previous literature and anecdotal evidence on junk fees, we find that a greater portion of the total price is allocated to obfuscated fees. Therefore, increased transparency leads to a reduction in the cleaning fee and an increase in the nightly price.

Proposition 1. *Suppose there are no competitive effects between the two types of hosts (i.e., $d = 0$). A marginal increase in the degree of transparency leads to a higher Host 1's equilibrium listing price and a lower Host 1's equilibrium cleaning fee, i.e., $\frac{dP_1^*}{d\lambda} > 0$ and $\frac{df^*}{d\lambda} < 0$.*

Moreover, when considering strategic interactions and, therefore, the overall effect of price transparency, we find that it leads to higher total prices, since both hosts end up setting a higher listing price in equilibrium. Here, we consider a discrete change in transparency, that is moving from no transparency to full transparency.

Proposition 2. *Suppose that there are competitive effects between the two types of hosts (that is, $d > 0$). Full price transparency (i.e., S moving from 0 to 1) leads to an increase in P_2 and, by strategic complementarity, to increases P_1 and f.*

Propositions 1 and 2 provide some important testable implications for online peer-to-peer markets. First, hosts not setting cleaning fees react to more transparency by raising their price since they were not observing the full price set by rival hosts. Moreover, hosts setting cleaning fees react to price transparency by directly reducing the cleaning fee and raising the price. Because their competitors set a higher price, by strategic complementarity, there is an increase in the cleaning fee and price for hosts of type 1. This generates our hypothesis that an increase in transparency could result in hosts actually increasing their prices. In addition, the total effect on cleaning fees is ambiguous, especially if only a few consumers were unaware of the cleaning fee prior to the policy change. Thus, a significant decrease in the cleaning fee would suggest that a significant number of consumers find the cleaning fee obfuscated.

4 The Effect on Cleaning Fees

To assess the impact of the transparency change on cleaning fees, we employ a difference-in-differences (DiD) design. Following negotiations with the European Commission, Airbnb introduced full price transparency for guests with EU IP addresses, but did not implement this change for non-EU IP addresses. The challenge in this setting is that the treatment variation primarily occurs on the demand side: travelers searching from within the EU are affected, while those searching from outside the EU are not. Unfortunately, we do not observe the location from which consumers search and book. However, we do observe the degree to which a listing is likely exposed to travelers from the EU vs non-EU countries. We would expect listings viewed and booked more frequently by travelers outside the EU to be less affected by the policy change. Therefore, our identification strategy leverages the differential impact of the policy change across listings based on their exposure to EU versus non-EU guests. Hosts whose listings typically attract more EU travelers should be more strongly affected by the policy, while those primarily catering to non-EU guests, whose cleaning fees remained obfuscated during the analysis period, are likely to experience a weaker effect.

For each listing, we create a measure of pre-2019 exposure to EU travelers based on the share of reviews received by listings within one kilometer that come from EU travelers. We classify EU and non-EU status of reviews using the self-reported home location of guests who have left a review. Although this is a self-reported measure, it is available for the majority of reviews.[17] This procedure gives us a measure of listing-specific, time-invariant, pre-policy exposure to EU travelers which should affect the degree to which the policy change impacts any given listing.

For our analysis, we discretize the EU exposure variable. Our treatment variable is set to one for any listing where the pre-policy share of nearby reviews from EU travelers exceeds the city-wide median, and zero otherwise. According to this measure, London has an average EU traveler share of 60%. Figure 3 presents the average exposure to EU travelers by LSOA in London. More central and touristic areas seem to be more exposed to non-EU travelers. This pattern indicates that neither the EU share of travelers nor the cleaning fee is randomly distributed. Therefore, we include geography-specific month as well as listing fixed effects in our analyses. The listing fixed effects account for cross-sectional, time-constant differences in cleaning fees and EU exposure. The geography-specific month fixed effects capture differences in seasonality in different areas of the city that are unrelated to the policy change.

We interact this treatment variable with a dummy variable that is equal to one for observations from

[17] For this approach to be valid, it is not necessary to assume that guests based in the EU have the same propensity to report their location or leave a review as non-EU guests. These propensities may differ; however, we require that any differences are consistent across the city to ensure meaningful comparisons between listings.

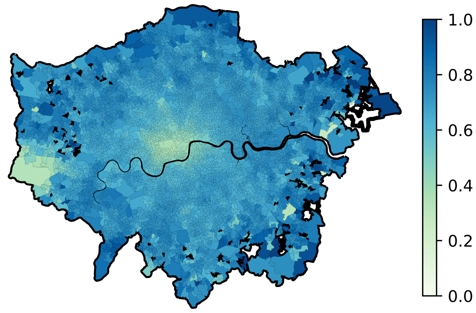


Figure 3. Average share of reviews from EU travelers by LSOA in London

January 2019 onward.[18] We regress the following equation:

$$y_{it} = c + \alpha \mathbb{1}(t \geq \text{Jan } 19) + \beta * eu_i * \mathbb{1}(t \geq \text{Jan } 19) + \mu_i + \gamma x_{it} + \varepsilon_{it}, \quad (1)$$

where eu_i denotes a dummy variable that is equal to one if the pre-2018 exposure to EU travelers is above the city-wide median, $\mathbb{1}(t \geq \text{Jan } 19)$ is the post-policy dummy, x_{it} are control variables that vary across specifications and y_{it} is the average asked cleaning fee of listing i in month t. Because we are interested in supply-side reactions to changes in price transparency, we analyze the *asked* cleaning fee. These fees may differ from the *booked* cleaning fee, which are the average fees for observed bookings. While the asked fees more directly measure supply-side behavior, the booked fees reflect equilibrium effects. We provide results using booked cleaning fees in Appendix C, where we see that the results using booked fees are in line with those using asked fees. We also find similar results on cleaning fees when we consider Paris and Rome (see Appendix F).

The interaction between the treatment variable and the post-policy dummy represents the treatment effect. We control for listing fixed effects μ_i to account for unobserved heterogeneity across listings that can be associated with their EU exposure as well as the level of the cleaning fee. In the most basic specification, we only include a linear time trend. Then, we add month fixed effects to account for city-level seasonality in cleaning fees. The post-policy dummy is effectively a year fixed effect because we restrict the analysis to 2018 and 2019 and the dummy is equal to one for observations in 2019. Hence, the month fixed effects together with the post-policy dummy are collinear with the linear time trend, and we cannot estimate them all

[18] The negotiations between the European Commission and Airbnb started in July 2018 when Airbnb was called to present prices more transparently. In September 2018, Airbnb committed to introduce price transparency from January 2019 at the latest. It is possible that the platform had started testing different fee display schemes between July 2018 and January 2019 which could possibly result in effects appearing even before January 2019. If this is the case, this would attenuate our results. Hence, our DiD estimates can be seen as a lower bound of the full effect. Such anticipatory effects would also show up as diverging pre-trends in our event study analyses.

jointly. To allow for different patterns of seasonality in different geographies, we also include specifications which include geography-specific month fixed effects. We include specifications using both larger and more granular geographic units.[19]

Table 2. DiD for asked cleaning fees

	(1)	(2)	(3)	(4)
Post-policy	0.423***	1.949***	1.970***	1.991***
	(0.0520)	(0.0610)	(0.0625)	(0.0645)
Post-policy X High EU	-0.603***	-0.603***	-0.648***	-0.673***
	(0.0726)	(0.0726)	(0.0762)	(0.0798)
Linear time trend	0.127***	0	0	0
	(0.00342)	(.)	(.)	(.)
Constant	27.29***	32.69***	32.69***	32.69***
	(0.159)	(0.0203)	(0.0203)	(0.0207)
Listing FEs	✓	✓	✓	✓
Month FE		✓	✓	✓
Large geo-month FEs			✓	
Small geo-month FEs				✓
Adj. R^2	0.98	0.98	0.98	0.98
Avg. cleaning fee	33.53	33.53	33.53	33.53
Obs.	1,030,459	1,030,459	1,030,459	1,030,459

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

Table 2 presents the results from these DiD regressions.[20] In general, cleaning fees have been increasing as evidenced by the positive linear time trend and the positive post-policy coefficient α. However, across all specifications, our DiD estimates show a statistically significant negative coefficient β. This result implies that for listings with above-median exposure to EU travelers, the cleaning fee has not increased as much after the introduction of price transparency as for other listings. In Column (1), we show results in the presence of a linear time trend. In Column (2), month fixed effects are added, whereas in Columns (3) and (4), we include geography-month fixed effects.

The coefficient of interest is *Post-policy* $\times$ *High EU* (β), which gives the average treatment effect for a listing with above-median exposure to EU travelers compared to a listing with below-median EU exposure. The results suggest that listings with above-median exposure to EU travelers reduce their cleaning fee by 0.6 to 0.7 GBP on average after the policy change. Since the average cleaning fee is approximately 34 GBP, this reduction amounts to approximately two percent of the average cleaning fee.

To check the parallel trends assumption, we also include results from event study regressions corre-

[19]The larger geographical units are boroughs (local authority districts) and the smaller geographical units are LSOAs.

[20]We implement the regressions using the *reghdfe* package in Stata, as described in Correia (2016).

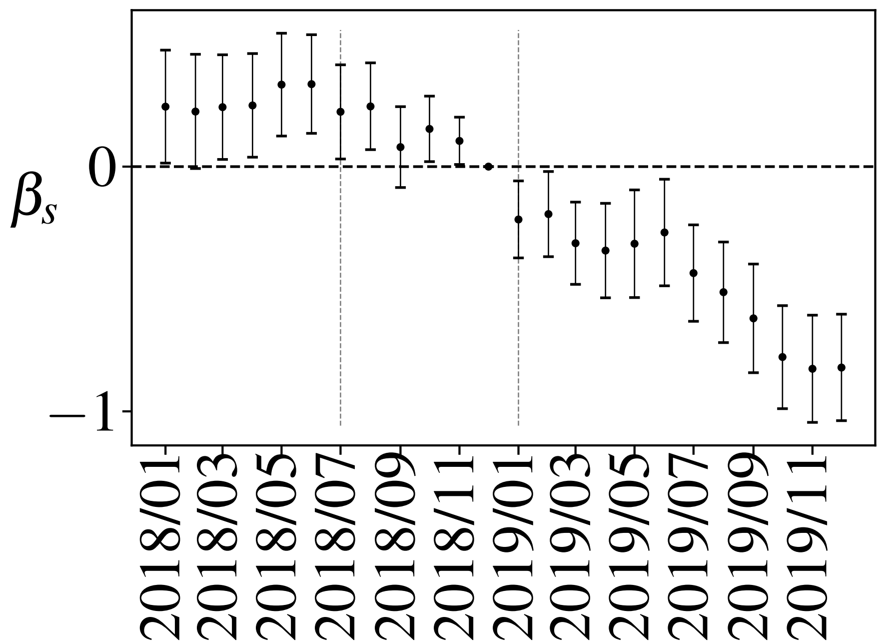


Figure 4. Event study analysis for the asked cleaning fee. The regressions include listing as well as geography-month fixed effects. Standard errors are clustered on the listing level. Bars show 95% confidence intervals.

sponding to column (3) in Table 2. Specifically, we estimate the following equation:

$$y_{it} = c + \sum_s \{\alpha_s \mathbb{1}(t = s) + \beta_s * eu_i * \mathbb{1}(t = s)\} + \mu_i + +\zeta_{g(i)t} + \varepsilon_{it}\,, \tag{2}$$

where the sum is over all the months in our sample and $\zeta_{g(i)t}$ are geography-month fixed effects. Figure 4 presents the coefficients β_s from the event study analysis. The results show that listings began reducing the cleaning fees following the full implementation of the price transparency in January 2019. Prior to the European Commission's call in July 2018, the conditional trends in cleaning fees are parallel across the treatment and control groups. There may be some evidence of a reaction starting in September 2018 and before the full implementation in January 2019. These reactions would be in line with hosts anticipating the policy change or Airbnb experimenting with parts of the website before fully implementing the policy change (recall that Airbnb committed to fully implementing price transparency by the end of the year in September 2018). However, the main drop happens after January 2019 which is when the policy is fully implemented by Airbnb. We obtain very similar results when considering the booked instead of the asked cleaning fee (see Appendix C) and when considering Paris and Rome (see Appendix F).

5 The Effect on Prices

We now turn our attention to how the policy change affected prices on Airbnb. In the previous section, we showed that listings that are likely more strongly affected by the policy change due to their exposure to EU travelers reduce their cleaning fees relative to those who are less exposed to travelers from the EU. Such a reduction in the cleaning fee is in line with rational hosts adjusting their optimal prices, taking into account that consumers are now more attentive to the fee than before. This result is also in line with Proposition 1. However, because Airbnb is a peer-to-peer platform, some hosts may face market frictions (e.g., inattention or search costs) that render them unaware of their direct competitors' fees as long as they are shrouded.

Recall the mechanism proposed in Section 3: Consider a host who analyzes competitors' prices by searching for similar listings nearby. Before the policy change, this host would only see the nightly rates, with additional fees hidden unless they clicked through each listing. After the policy change, they can see the full price per night, including all fees. Consequently, competitors' listings appear more expensive post-policy, potentially inducing the host to raise their own prices. Moreover, we have already observed that around one-third of listings never present a cleaning fee. This evidence is consistent with an official Airbnb statement in 2021, which noted that "among active Airbnb listings worldwide, 45 percent do not charge a cleaning fee. For listings that do charge a cleaning fee, the fee averages less than 10 percent of the total cost of the reservation."[21] This finding suggests that many hosts are not incorporating cleaning fees into their pricing strategy and may also be inattentive to competitors' fees when setting their prices.

Following the above argument, we would expect to see price increases for listings that appear more affordable as they move from the opaque to the transparent fee scheme. To explore this hypothesis and study the effect of price transparency on nightly prices, we propose the following analysis. For each listing i in month t, we calculate the following price difference:

$$\Delta P_{i,t}^{shrouded} = P_{i,t} - \tilde{P}_{i,t},$$

where $P_{i,t}$ is the average asked price per night of listing i in month t, and $\tilde{P}_{i,t}$ is the average asked price per night of comparable listings in the same month. This difference indicates how the price (net of fees) of listing i compares to its competitors in month t. Next, we define:

$$TP_{i,t} = P_{i,t} + \frac{f_{i,t}}{n_{i,t}}$$

[21] For the full statement, see: https://news.airbnb.com/fee-transparency-on-airbnb/ (last accessed: November 18, 2024).

as the total price per night (including the cleaning fee $f_{i,t}$, normalized by a measure of average length of booking $n_{i,t}$) of listing i in month t, and calculate the difference:

$$\Delta P_{i,t}^{unshrouded} = TP_{i,t} - \tilde{TP}_{i,t}.$$

This measure captures how the total price of listing i compares to that of its competitors in month t. The difference:

$$\delta_{i,t} = \Delta P_{i,t}^{shrouded} - \Delta P_{i,t}^{unshrouded}$$

captures the impact of price transparency on the perceived relative affordability of listing i in month t.

Notably, $\delta_{i,t} = \tilde{TP}_{i,t} - \tilde{P}_{i,t} - \frac{f_{i,t}}{n_{i,t}}$ is driven by the difference between the listing's own fee and the average fee of comparable listings. The larger $\delta_{i,t}$, the more affordable listing i would be perceived due to price transparency in month t.

Note that cleaning fees on Airbnb apply to the entire stay. Therefore, obtaining the cleaning fee per night requires normalization by a relevant number of nights. We implement this normalization by dividing the cleaning fee by the average duration of stay in 2018 for every listing. If we do not observe any bookings for a given listing, we divide by the minimum nights requirement instead. If we do not observe a minimum nights requirement, we divide by one, effectively assuming a relevant length of stay of one night.[22]

To calculate $\delta_{i,t}$, we need to define relevant comparison prices $\tilde{P}_{i,t}$ and $\tilde{TP}_{i,t}$. These should be the average prices of comparable listings in the same period. We estimate these benchmark prices by estimating linear regressions of the price (net of the fee and including the fee, respectively) on whether a listing is hosted by a "Superhost", its number of reviews, whether it is instant bookable, and whether it is an entire home. We also absorb geography and month fixed effects. We focus on 2018 to calculate a measure of pre-policy prices. Based on these regressions, we obtain predicted prices for listings with similar observable characteristics. $\Delta P_{i,t}^{shrouded}$ and $\Delta P_{i,t}^{Unshrouded}$ are then the residuals obtained from these regressions. Finally, we take the 2018 average of $\delta_{i,t}$ for each listing i, denoted as δ_i, to measure the potential for price increases following the policy change.

The left panel of Figure 5 presents the distribution of δ_i for all listings in our sample. The figure shows that the distribution of δ_i is relatively symmetric and centered around zero with some large outliers. The right panel of Figure 5 presents the distribution of δ_i for those listings that never set a positive cleaning fee. For these listings, δ_i is mostly positive, which implies that they become more affordable when the fees are

[22] An alternative way to account for this issue is to restrict the analysis to listings with a minimum nights requirement of one night only and to use the observed cleaning fee in $TP_{i,t}$. This restriction reduces the sample substantially, but the results are qualitatively and quantitatively similar. We report the results in Appendix D.

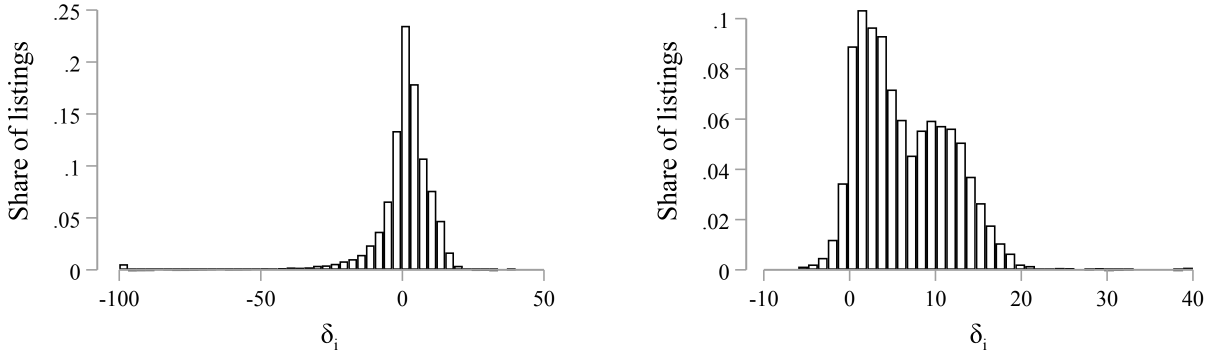


Figure 5. Distribution of δ_i for entire sample (left) and for zero fees only (right). Values are windsorized at -100 and 40 for better readability.

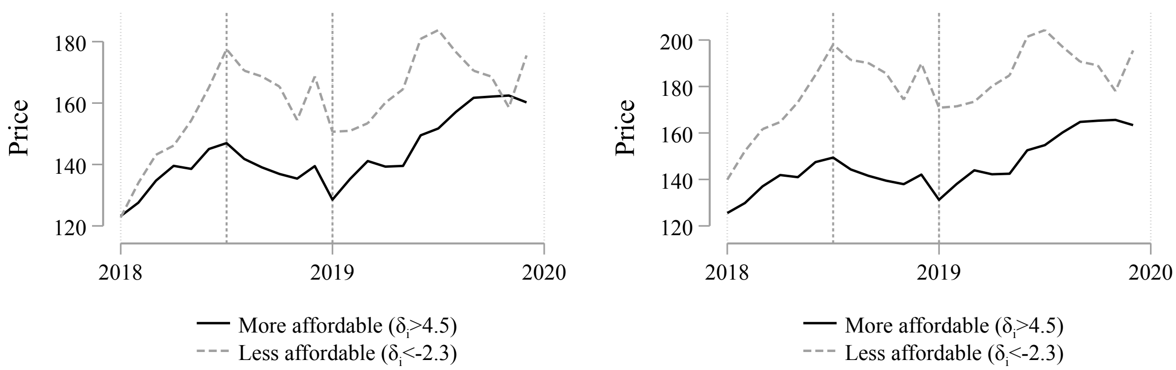


Figure 6. Prices net of fee (left) and including of the fee (right) over time by high and low δ_i

unshrouded, at least from the perspective of a host or guest who ignores the cleaning fee when it is shrouded.

Figures 6 present prices net of the cleaning fee and inclusive of it, in the left and right panels respectively, over time for listings grouped into two categories based on their value of δ_i. Recall that $\delta_i > 0$ can be interpreted as the listing being more affordable with price transparency. Conversely, listings with a negative δ_i appear less affordable with price transparency. Therefore, we define "more affordable" as those listings with $\delta_i > 4.5$, which is the 75th percentile of δ_i. We call those listings with $\delta_i < -2.3$, which is the 25th percentile of δ_i, "less affordable". In this figure, we exclude listings whose δ_i falls within the inter-quartile range because these are the listings whose relative price does not substantially change with and without price transparency.

The left panel of Figure 6 displays the prices (net of fees). For half a year prior to the full implementation of price transparency in January 2019, prices for both the "more affordable" and "less affordable" listings developed fairly in parallel, with the "less affordable" listings having become relatively more expensive between January and July 2018. From January 2019 onwards, prices converge as the "more affordable" listings become more expensive. When looking at total prices including fees in the right panel of Figure 6, the shape of the curves looks similar, but the curve for "less affordable" listings is shifted upwards. These patterns suggest that "more affordable" listings may have indeed adjusted their prices upwards following the policy change.

Next, we estimate DiD regressions and event study specifications similar to those described in Equations (1) and (2), except that we use prices as outcomes and a treatment dummy that is equal to one for listings classified as "more affordable". Table 3 shows the difference-in-differences results for different specifications. We report the results for both the price net of the fee (columns (1) to (4) as well as inclusive of the fee (columns (5) to (8)). The results suggest that listings appearing more affordable under price transparency (i.e., those with a δ_i in the highest quartile of the distribution) increase their prices following the introduction of price transparency compared to other comparable listings. After the policy change, these "more affordable" listings become approximately 8 GBP more expensive. This finding holds regardless of whether we focus on the price net of the fee or the price including the fee.

To assess whether the parallel trends assumption is likely to hold, we also run event study regressions. Figure 7 reports the estimated event study coefficients β_s. The results do not suggest a violation of the assumption of parallel conditional pre-trends. The estimates are noisy, but again suggest that prices have increased relatively more for listings that appear more affordable under full price transparency. It is important to note that, in 2018, the average price per night (net of the fee) of a listing classified as "more affordable" was about 131.51 GBP. Therefore, an average increase of 8 GBP amounts to an average price increase of about six percent.

Table 3. Difference-in-differences results for prices

	Outcome: Price net of fee				Outcome: Price including fee			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-policy	-11.17***	6.526***	6.491***	6.543***	-10.92***	6.702***	6.655***	6.719***
	(0.642)	(0.480)	(0.481)	(0.497)	(0.596)	(0.474)	(0.475)	(0.497)
Post-policy X "More affordable"	7.518***	7.518***	7.784***	7.841***	7.584***	7.590***	7.915***	7.930***
	(1.680)	(1.680)	(1.680)	(1.686)	(1.706)	(1.706)	(1.702)	(1.705)
Linear time trend	1.483***	0	0	0	1.482***	0	0	0
	(0.0468)	(.)	(.)	(.)	(0.0423)	(.)	(.)	(.)
Constant	51.22***	114.3***	114.3***	114.2***	59.16***	121.8***	121.8***	121.9***
	(2.075)	(0.417)	(0.417)	(0.419)	(1.844)	(0.222)	(0.222)	(0.227)
Listing FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FE		✓	✓	✓		✓	✓	✓
Large geo-month FEs			✓				✓	
Small geo-month FEs				✓				✓
Adj. R^2	0.85	0.85	0.85	0.84	0.73	0.74	0.74	0.72
Avg. total price	119.47	119.47	119.47	119.47	125.37	125.37	125.37	125.49
Obs.	1,030,459	1,030,459	1,030,459	1,030,459	860,709	860,709	860,709	859,245

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

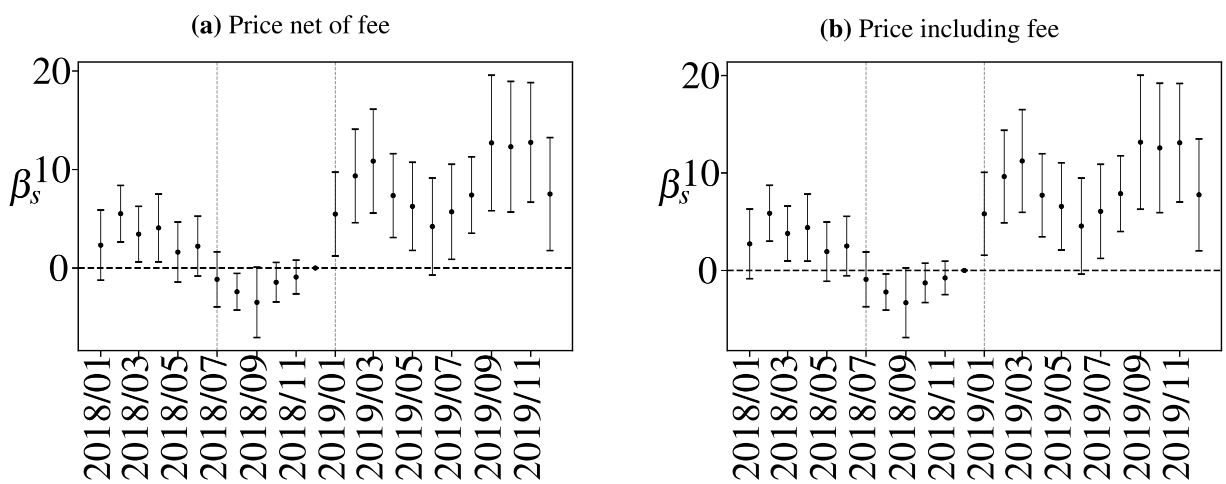


Figure 7. Event study for asked prices. Includes linear time trend and listing as well as geographic area-month FEs. Standard errors clustered on listing level. Bars show 95% confidence intervals.

6 London vs New York City

One concern in our design is that listings in the treatment and control groups may compete with each other. If that is the case, a competitor's treatment status could influence a focal listing's behavior, potentially violating the Stable Unit Treatment Value Assumption (SUTVA). Arguably, such spillovers are more likely to affect pricing decisions, which may indeed be affected by competitors' actions. Instead, the decision to set or adjust a cleaning fee is likely driven primarily by listing-specific factors, such as actual cleaning costs and the listing's own demand (e.g., exposure to EU travelers). In addition, information about the magnitude of competitors' cleaning fees remains relatively opaque even after the policy change. Although hosts can now easily see the total price per night inclusive of the fee, in order to see the decomposition of that price into nightly base price and fees, hosts would still need to browse through their competitors' listing pages (see Figure 1).

In this section, we provide additional evidence that relies on a different identification strategy. Instead of defining control and treatment based on listing-level exposure to EU travelers, we compare listings in London to New York City. The idea behind this strategy is that listings in London should be exposed to more travelers from the EU and hosts in London are likely more attentive to the policy change as well. Moreover, hosts in New York City do not experience the unshrouding of fees on the local version of the Airbnb website. Thus, New York-based hosts are less likely to adjust their prices in response, unlike their counterparts in London, as demonstrated in our earlier analysis.

Finally, listings in London are most likely not competing with listings in New York City, and the violation of SUTVA is less of a concern with this approach. However, because the treatment now applies on the city level, it becomes more difficult to account for city-level trends, especially in the event study specification.

6.1 The Effect on Cleaning Fees

We begin by analyzing the effect of the policy change on cleaning fees in London compared to New York City. For the difference-in-differences specifications, we estimate a similar equation as described in Equation (1). The main difference is that we now define the treatment variable not based on the share of nearby reviews from EU travelers, but instead the treatment variable is equal to one for listings in London and zero for those in New York City. In specifications with fixed effects by geographical months, we use boroughs as the geographical units. In the specifications with small geography-month fixed effects, we use the LSOA in

London and Neighborhood Tabulation Areas (NTA) for New York City.[23]

Table 4 reports the results for the analysis regarding the cleaning fee. Airbnb listings in London decreased their cleaning fees by an average of about 1.2 to 1.4 GBP after the policy compared to those in New York. The average cleaning fee in our London sample is approximately 33.53 GBP (see Table 1). Hence, this reduction amounts to about 4% of the average cleaning fee.

Table 4. DiD for asked cleaning fees (London vs NYC)

	(1)	(2)	(3)	(4)
Post-policy	0.670***	2.937***	-0.988***	3.096***
	(0.0626)	(0.0744)	(0.151)	(0.0801)
Post-policy X London	-1.192***	-1.192***	-1.446***	-1.430***
	(0.0805)	(0.0805)	(0.0883)	(0.0896)
Linear time trend	0.189***	0	0.341***	0
	(0.00325)	(.)	(0.0135)	(.)
Constant	38.96***	42.45***	36.16***	42.53***
	(0.0744)	(0.0191)	(0.254)	(0.0193)
Listing FEs	✓	✓	✓	✓
Month FE		✓	✓	✓
Large geo-month FEs			✓	
Small geo-month FEs				✓
Adj. R^2	0.98	0.98	0.98	0.98
Avg. cleaning fee	43.54	43.54	43.54	43.62
Obs.	1,633,621	1,633,621	1,633,621	1,629,369

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

Next, we estimate an event study regression similar to the one described in Equation (2). Again, the treatment variable is now equal to one if a listing is in London and zero if it is in New York. Note that because the treatment assignment no longer varies within the city, we cannot separately control for geography-month fixed effects. Hence, we report a specification that only includes a linear time trend on top of the listing fixed effects. This specification corresponds to the one reported in column (1) of Table 4.

Figure 8 suggests that the cleaning fee developed parallelly conditional on covariates in New York City and London in the months prior to the full implementation of price transparency in January 2019. However, it also points to possible diverging pre-trends in the first half of 2018. These pre-trends may be driven by the fact that in this event study specification, we cannot account for geography-specific seasonality due to the treatment variation being on the city level. However, note that in the difference-in-differences specifications reported in columns (3) and (4) we do control for geography-month fixed effects. That is possible because the DiD specification does not include all lead-lag variables, but only one post-policy dummy.

[23]We keep the original currencies for each city (GBP for London and USD for New York) to avoid discrepancies caused by exchange rate fluctuations. Across all specifications, we employ listing fixed effects. Thus, fixed differences related to the currency levels should not confound our analysis.

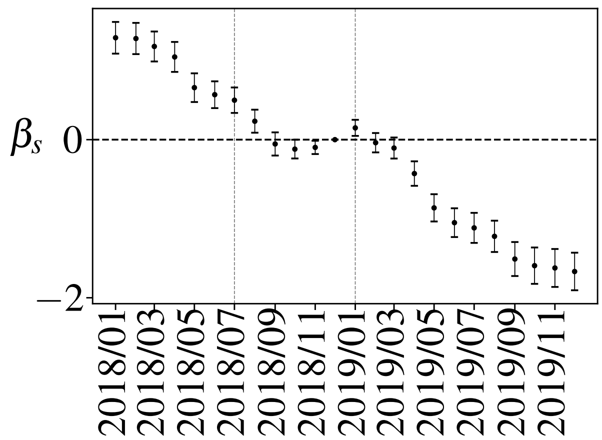


Figure 8. Event study analysis for the asked cleaning fee (London vs NYC). The regressions include listing fixed effects and a linear time trend. Standard errors are clustered on the listing level. Bars show 95% confidence intervals.

6.2 The Effect on Prices

To assess how the policy change affected asked prices in London compared to New York City, we conduct an analysis similar to the one reported in Section 5. We begin by calculating δ_i as previously described. However, we now calculate it separately for each city. Next, we classify listings as "more affordable" if their δ_i is larger than the 75th percentile in the city and "less affordable" if their δ_i is below the 25th percentile in the city.

The analysis in Section 5 suggests that high-δ ("more affordable") listings increased their prices relative to other listings after the policy change. The mechanism we suggest for this result is that hosts that were not attentive to their competitors' fees before the policy change can now more easily observe the total price inclusive of the fee, realize their own listings are more affordable, and adjust their prices upward. This mechanism requires that these hosts are also affected by the treatment. However, hosts based in New York City are not affected by the treatment as they would still be shown the prices net of the fee when searching on Airbnb. Hence, while "more affordable" listings in London increase their prices after the policy change, we would not expect "more affordable" listings in New York City to do the same. Therefore, in this section, we compare "more affordable" and "less affordable" listings between the two cities and Figure 9 presents descriptive figures comparing the average price (net of fees) over time for "more affordable" and "less affordable" listings in London versus New York City. Figure 9a suggests that after the policy change, prices of "more affordable" listings may have increased a bit more steeply in London, leading to prices slowly converging between the two cities. Figure 9b does not show such a pattern when focusing on "less affordable" listings.

(a) "More Affordable" Listings

(b) "Less Affordable" Listings

Figure 9. Prices net of fee over time comparing more and less affordable listings in London and New York City. "More affordable" are listings for which δ_i is larger than the city-level 75th percentile of δ_i. "Less affordable" are listings for which δ_i is smaller than the city-level 25th percentile of δ_i.

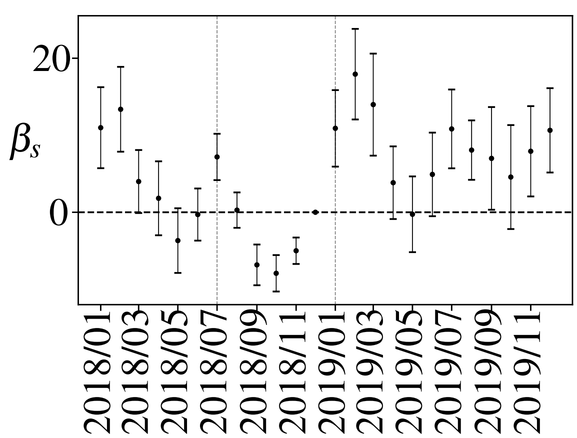
In terms of estimation results, Table 5 gives DiD estimates when comparing the net price per night for "more affordable" and "less affordable" listings in London and New York City. The results show that asked prices of "more affordable" listings in London increased by an average of 7 to 8 GBP per night compared to "more affordable" listings in New York City after the policy change (a 5% increase). Notably, when comparing the "less affordable" listings in the two cities, we do not observe a change in relative prices following the policy change. These results are in line with our mechanism in which "more affordable" listings would increase their prices after being able to see their competitors' total prices more easily, but "less affordable" listings do not react to the policy change.

Lastly, Figure 10 reports the corresponding event study estimates. Although estimates are noisy, Figure 10a confirms that the prices for "more affordable" listings in London have increased compared to those in New York City. Prices for "less affordable" listings do not show such a pattern – if anything, the results suggest a slight decrease in prices for "less affordable" listings in London compared to New York City.

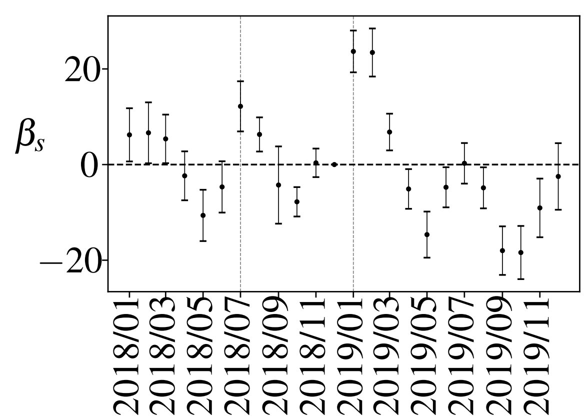
Table 5. Difference-in-differences results for prices net of fee (London vs NYC)

	"More affordable" listings				"Less affordable" listings			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-policy	-13.48***	5.803***	-13.93***	6.844***	-24.85***	10.10***	-31.51***	12.16***
	(1.082)	(1.014)	(2.212)	(1.092)	(1.336)	(1.092)	(6.379)	(1.229)
Post-policy X London	8.355***	8.384***	7.042***	6.694***	0.421	0.451	-2.371	-2.380
	(1.903)	(1.903)	(1.921)	(1.917)	(1.500)	(1.498)	(1.582)	(1.697)
Linear time trend	1.618***	0	1.721***	0	2.954***	0	3.616***	0
	(0.0721)	(.)	(0.194)	(.)	(0.0845)	(.)	(0.486)	(.)
Constant	113.1***	142.7***	111.2***	143.7***	114.0***	168.2***	102.0***	169.4***
	(1.365)	(0.430)	(3.625)	(0.428)	(1.688)	(0.338)	(8.807)	(0.363)
Listing FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FE		✓	✓	✓		✓	✓	✓
Large geo-month FEs			✓				✓	
Small geo-month FEs				✓				✓
Adj. R^2	0.75	0.75	0.75	0.74	0.72	0.72	0.72	0.70
Avg. total price	147.14	147.14	147.14	148.14	172.58	172.58	172.58	173.92
Obs.	329460	329460	329460	323434	329471	329471	329471	322544

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.



(a) "More Affordable"



(b) "Less Affordable"

Figure 10. Event study for the asked price net of the cleaning fee, comparing more affordable (left) and less affordable (right) listings in London versus New York City. "More affordable" are listings for which δ_i is larger than the city-level 75th percentile of δ_i. "Less affordable" are listings for which δ_i is smaller than the city-level 25th percentile of δ_i. Includes linear time trend and listing as well as year-month FEs. Standard errors clustered on listing level. Bars show 95% confidence intervals.

7 Total Policy Impact

Our results highlight that assessing the impact of the introduction of price transparency on a peer-to-peer platform can be complex. On the one hand, we find that some listings react to the increase in salience of the cleaning fee by reducing their cleaning fees. On the other hand, we observe that some (potentially different) listings react to the more transparent display of fees by raising their prices. A straightforward comparison of effect sizes might suggest that total prices increased, as the policy change appears to have a larger impact on nightly prices than on cleaning fees. However, this approach overlooks the fact that different sets of listings adjust their fees or prices in response to the policy change.

Furthermore, the analysis so far focused on supply-side reactions to the policy change. To evaluate the overall impact of the policy, it is important to also consider demand reactions. Accordingly, we now examine how the policy change influences booked prices, fees, and quantities. Ultimately, our aim is to assess the policy's effect on revenues. Let this effect be denoted as:

$$\Delta rev = rev' - rev, \tag{3}$$

where rev' denotes a listing's revenue after price transparency has been introduced and rev denotes a listing's counterfactual revenue had price transparency not been introduced. In our setting, revenue can be defined as $rev = (nP + f)Q$, where Q denotes the number of bookings, n denotes the average length per booking, P denotes the average booked nightly price, and f denotes the average booked cleaning fee. Given this definition, we can decompose Equation (3) as follows:

$$\Delta rev = \Delta Q(n'P' + f') + (Q' - \Delta Q)(n'\Delta P + \Delta nP' - \Delta n\Delta P + \Delta f)\,. \tag{4}$$

Appendix G shows the derivation. This decomposition allows us to understand how much of the impact of the policy change on revenues is due to changes in booked quantities or booked prices, correcting for the interaction of both.

Equation (3) contains several counterfactual expressions, which we can estimate using methods outlined in the previous sections. We estimate ΔQ by using the DiD framework to assess how the policy change affected the number of bookings. We estimate Δn as the policy's impact on the average booking length. We estimate ΔP as the policy's impact on booked nightly prices (net of the fee). Finally, we estimate Δf as the treatment effect of the policy change on booked cleaning fees. As P', f', q', and n', we use the average booked prices and fees, number of bookings, and booking length, focusing on the treatment group in 2019

Table 6. Number and share of observations by listing group

	EU exposure		
	Above-median	Below-median	Total
"More affordable"	84,246 9,79%	130,352 15.14%	214,598 24.93%
Not " more affordable"	334,177 38.83%	311,934 36.24%	646,111 75.07%
Total	418,423 48.61%	442,286 51.39%	860,709 100%

(i.e. after implementation of price transparency).

For our analysis, we divide the listings into four groups based on their exposure to EU travelers (above or below the median) and whether they are classified as "more affordable" in Section 5 according to our definition of δ_i. Table 6 shows the number and share of observations for each type of listing in our price analysis. Recall that the two treatment criteria considered in our analysis are whether a listing has above-median exposure to EU travelers and whether a listing's 75th percentile in which case we label it as "more affordable". These two treatment definitions are not mutually exclusive, i.e., a listing can be both exposed to a large share of EU travelers and also be more affordable. However, Table 6 shows that the listings that meet both treatment criteria account for only about 10 percent of the sample. Approximately 40 percent of observations are listings with above-median EU exposure but not classified as "more affordable". About 15 percent of observations are listings that are "more affordable" but do not have above-median EU exposure, whereas approximately 36 percent of listings have neither above-median exposure to EU travelers nor are considered "more affordable".

To compute our counterfactual values, we treat the group of non-"more affordable", below-median EU exposure listings as the control group. For these listings, we assume that $rev' = rev$ and, hence, $\Delta rev = 0$. For the other listings, instead, we obtain counterfactual values by regressing outcome variables based on the treatment variables' interactions with the post-policy dummy. In particular, we estimate the following

Table 7. Triple-DiD regressions on equilibrium outcomes

Dependent variable	(1) Nightly price	(2) Cleaning fee	(3) Bookings	(4) Booking length
Post-policy (α)	3.992***	2.327***	-4.739***	-0.459***
	(0.548)	(0.0854)	(0.0754)	(0.0217)
... X High EU (β_{EU})	-1.760**	-0.738***	2.264***	0.113**
	(0.563)	(0.103)	(0.0962)	(0.0360)
... X "More affordable" (β_{ma})	3.986***	-0.0427	-0.541***	-0.849***
	(0.703)	(0.149)	(0.136)	(0.0510)
... X High EU X "More affordable" (β_X)	-1.913*	0.574*	-1.485***	-0.189*
	(0.821)	(0.234)	(0.200)	(0.0895)
Constant	111.8***	32.19***	13.44***	5.994***
	(0.137)	(0.0217)	(0.0178)	(0.00728)
Adj. R^2	0.08	0.98	0.19	0.22
Avg. DV	113.53	33.07	11.82	5.73
Obs.	533,601	532,907	860,709	533,601

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

equation:

$$
\begin{aligned}
y_{it} = c &+ \alpha \mathbb{1}(t \geq \text{Jan 19}) \\
&+ \beta_{EU} * eu_i * \mathbb{1}(t \geq \text{Jan 19}) \\
&+ \beta_{ma} * ma_i * \mathbb{1}(t \geq \text{Jan 19}) \\
&+ \beta_X * eu_i * ma_i * \mathbb{1}(t \geq \text{Jan 19}) \\
&+ \mu_i + \gamma x_{it} + \varepsilon_{it},
\end{aligned} \tag{5}
$$

where y_{it} are average booked prices, average booked cleaning fees, average number of bookings, or average booking length. We use the estimated coefficients for β_{EU} as ΔP, Δf, ΔQ, and Δn in Equation (4) for non-"more affordable", high-EU-exposure listings. Similarly, we use the estimated coefficients for β_{ma} for "more affordable", low-EU-exposure listings. Finally, we use $\beta_{EU} + \beta_{ma} + \beta_X$ for listings that are both high-EU-exposure listings and "more affordable" listings. As in our previous estimates, we include geography-month fixed effects.

In Table 7 we report the results of these regressions, and we see that our previous findings from Sections 4 and 5 are largely confirmed. Column (3) shows that the average booked cleaning fee for listings with high-EU exposure (that are not also "more affordable") decreased by an average of 0.74 GBP, in line with the decrease of about 0.6 to 0.7 GBP in asked fees reported in Table 2. Furthermore, the booked cleaning fee of “more affordable” listings that are not highly-exposed to EU travelers does not change in response to the policy change. Column (2) shows that the average booked price per night for “more affordable” listings increased by approximately 4 GBP, which aligns with the average increase in asking prices of about 8 GBP reported in Table 3. These results also show that consumer reactions play a crucial role in determining the difference between booked and asked prices. While the impact on booked fees is similar to that on asked fees, the effect on booked prices is attenuated because consumers are less likely to book listings that raise their prices excessively.

In addition to confirming the findings of the previous sections, Table 7 also provides a range of new results. However, these should be interpreted with caution. While the event studies presented in Sections 4 and 5 support the conditional parallel trends assumption necessary to interpret the DiD estimates as causal, we have not provided similar evidence for some of these additional outcomes and treatment definitions. Appendix H shows the event study coefficients corresponding to Table 7. That said, one notable result is that the average length of bookings for “more affordable” listings shows no evidence of diverging pre-trends and decreases quite markedly after the policy change. This result suggests that the demand for “more affordable” listings decreased after price transparency, and this could be due to the increase in the nightly price that we documented for these listings.

To calculate the impact of price transparency using the ideas described in Equation (4), we need the estimated coefficients from Table 7 and mean values of the various outcome variables for each listing group in 2019. Table 8 provides these means and the number of underlying observations. However, some of these expressions in Equation (4) would be based on estimates for which the parallel trends assumption may be problematic. Therefore, we focus on the expressions for which the event studies do not suggest violation of conditional parallel pre-trends to interpret the results conservatively and assign a value of zero otherwise (see Appendix H). Table 9 reports the calculations for the change in booked prices for “more affordable” listings, the decrease in booked cleaning fees for high-EU-exposure listings, and the decrease in booking length for “more affordable” listings. For example, to calculate how revenues change as a result of a change in nightly prices ($n'\Delta P$) for non-high-EU-exposure and “more affordable” listings, we multiply the average booking length in 2019 (5.35) for these listings by the increase in booked nightly prices due to the policy change (3.986).

This conservative interpretation suggests that high-EU-exposure listings experience a small average decrease in revenues of 2.10 GBP per month due to the decrease in average booked cleaning fees of 0.74 GBP, combined with an average of about three bookings per month. Revenues of “more affordable” listings decrease by about 307 GBP per month. While the revenues increase by 21.33 GBP due to the higher booked

Table 8. Means and underlying number of observations by listing group in 2019

Dependent variable	Nightly price	Cleaning fee	Bookings	Booking length
High EU	73.17 89,281	26.05 89,190	2.85 138,560	5.72 89,281
“More affordable”	157.03 31,438	19.45 31,421	2.83 51,920	5.35 31,438
High EU X “More affordable”	97.98 19,437	14.93 19,425	2.29 33,740	5.55 19,437
Control	142.76 93,442	50.12 93,353	3.77 131,670	5.04 93,442
Total	114.36 233,598	33.86 233,389	3.13 355,890	5.38 233,598

Notes: Each cells shows the mean in 2019 at the top and the underlying number of observations at the bottom.

Table 9. Values for expressions in Equation (4)

	$\Delta Q(n'P'+f')$	$n'\Delta P$	$\Delta nP'$	$\Delta n\Delta P$	$n'\Delta P+\Delta nP'-\Delta n\Delta P+\Delta f$	Δrev
High EU	0.00	0.00	0.00	0.00	-0.74	-2.10
“More affordable”	0.00	21.33	-133.32	-3.38	-108.61	-307.36
High EU X “More affordable”	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Calculations based on estimates in Table 7 and means from Table 8. A 0.00 is assigned whenever event studies suggest violation of the parallel trend assumptions.

prices per night, the revenues decrease by much more because the average booking length decreases due to the higher prices. Because we have 138,560 observations for high-EU-exposure listings in 2019 and 51,920 observations for "more affordable" listings in 2019, these numbers suggest an overall decrease in revenue due to the policy change of about 291,433 GBP for high-EU-exposure listings and 15,958,349 GBP for "more affordable" listings.

There are several explanations why the revenues of "more affordable" listings might decrease following the policy. First, if they only check stays of one or two nights (shorter than the actual average stay), they might perceive themselves as even more under-priced than they actually are and thus substantially increase their prices. This explanation would suggest that these hosts have over-corrected their prices following the policy change. Second, these hosts may be comfortable with shorter stays at a higher price, especially if their costs are significant. For example, if cleaning costs increase with the length of stay, it may be more profitable for these hosts to have shorter bookings, even if that means lower revenues. The question with this explanation would be why they had not already increased their prices prior to the policy change. One reason could be that they were restricted because competitive dynamics were different prior to the policy. Less affordable listings, which guests perceived as having low per-night prices, were too formidable as competitors for short stays. Furthermore, these hosts likely did not realize that the low per-night prices did not reflect the higher overall prices that included the cleaning fees. This explanation would suggest that the observed decrease in revenue does not necessarily correspond to a decrease in profits.

8 Further Results

In this section, we present a series of extensions and additional results. First, we examine Superhosts, who are more likely to be professionals. Second, given that hosts have multiple tools to influence guests' decisions, we investigate whether they respond to the policy by altering the minimum-night requirements for bookings, which could indicate the use of the cleaning fee as a screening device.

8.1 Superhosts

More professional hosts are likely to be more attentive to policy changes such as the introduction of fee price transparency. Therefore, we expect to find larger effects on cleaning fees when focusing the analysis on more professional hosts. One possible measure of host professionalism is the "Superhost" indicator that hosts on Airbnb can earn. Superhost status is assigned by Airbnb and can be earned based on a high number of reservations, high response rate, low host cancellation rates, and high rating.[24] The status is assessed every three months based on the preceding 12 months. Therefore, the status can vary within hosts.

In our sample, about 22 percent of the hosts are Superhosts at some point. These Superhosts contribute about 30 percent of the observations, which implies that they are more active than non-Superhosts. Moreover, 77 percent of Superhosts do set a cleaning fee, contrary to 72 percent of non-Superhosts. This suggests Superhosts are more likely to be more attentive to the change in platform design and, as a result, could react with a larger reduction in the cleaning fee. We replicate the main DiD analysis of Section 4 for Superhosts only and we present the main results in Table 10. The results suggest that Superhost listings with above-median exposure to EU travelers reduce their cleaning fee by about 1 GBP on average after the policy change compared to Superhost listings with below-median exposure to EU travelers. As expected, Superhosts with greater exposure to EU travelers are more responsive to the policy on average.

Table 10. DiD for asked cleaning fees (Superhosts only)

	(1)	(2)	(3)	(4)
Post-policy	0.690***	2.124***	2.166***	2.190***
	(0.120)	(0.153)	(0.157)	(0.178)
Post-policy X High EU	-0.971***	-0.971***	-1.046***	-1.085***
	(0.179)	(0.179)	(0.189)	(0.216)
Linear time trend	0.119***	0	0	0
	(0.00856)	(.)	(.)	(.)
Constant	26.77***	31.85***	31.85***	31.84***
	(0.408)	(0.0571)	(0.0571)	(0.0629)
Listing FEs	✓	✓	✓	✓
Month FE		✓	✓	✓
Large geo-month FEs			✓	
Small geo-month FEs				✓
Adj. R^2	0.98	0.98	0.98	0.98
Avg. cleaning fee	32.80	32.80	32.80	32.80
Obs.	154,477	154,477	154,477	154,477

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

8.2 Cleaning Fee as a Screening Device

One important feature of the cleaning fee on Airbnb is that it applies per booking whereas the base price applies per night. As such, hosts on Airbnb can essentially set two-part tariffs and use the cleaning fee

[24] For more details, see: https://www.airbnb.co.uk/help/article/829 (last accessed: December 13, 2024).

Table 11. DiD for minimum nights

	(1)	(2)	(3)	(4)
Post-policy	-0.0623	0.479***	0.479***	0.476***
	(0.0647)	(0.0511)	(0.0513)	(0.0526)
Post-policy X High EU	0.163	0.162	0.166	0.161
	(0.107)	(0.107)	(0.107)	(0.109)
Linear time trend	0.0456***	0	0	0
	(0.00379)	(.)	(.)	(.)
Constant	0.535**	2.465***	2.465***	2.471***
	(0.169)	(0.0204)	(0.0205)	(0.0212)
Listing FEs	✓	✓	✓	✓
Month FE		✓	✓	✓
Large geo-month FEs			✓	
Small geo-month FEs				✓
Adj. R^2	0.26	0.26	0.27	0.25
Avg. min. nights	2.69	2.69	2.69	2.70
Obs.	506,898	506,898	506,898	500,690

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

to price discriminate between travelers based on the length of their stay. Price transparency can alter this strategy: by making the cleaning fee more salient, it becomes a more effective tool for screening travelers ex ante based on their desired length of stay. As a result, the minimum-night constraints may be relaxed, and hosts might find it optimal to reduce the minimum required length of stay instead.

To account for this possibility, we perform the same analysis as for the effect on cleaning fees (see Section 4), but use the minimum required length of stay as an outcome variable. That means we analyze how listings with above-median exposure to EU travelers changed their required minimum nights for bookings after the policy change compared to listings with below-median exposure to EU travelers. Table 11 reports the results of the DiD regression, and Figure 11 shows the results of the event study regression corresponding to column (3) of Table 11. There is no evidence that the policy change affected the required minimum nights on average. This null result suggests that the hosts did not use the cleaning fee to screen consumers based on their desired length of stay. This finding further supports previous evidence that hosts reacted to the policy by only slightly reducing the cleaning fee and is in line with the hypothesis that the cleaning fee is mainly used to cover cleaning costs, rather than as a screening tool.

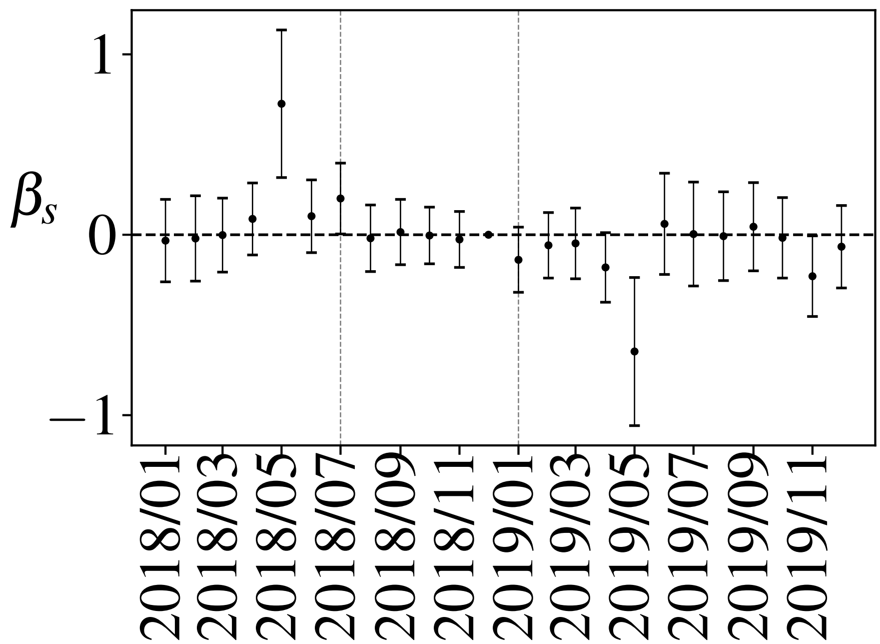


Figure 11. Event study analysis for the minimum nights. The regressions include listing as well as geography-month fixed effects. Standard errors are clustered on the listing level. Bars show 95% confidence intervals.

9 Conclusion

With increased scrutiny on junk fees by antitrust authorities and policymakers, assessing how price transparency impacts market outcomes is pivotal. Most analyses so far have focused on add-on and junk fees in the context in which some prices were obfuscated and deceptively used by the platform's owner (or sellers) to extract rents from inattentive consumers.

Our study provides new insights into the impact of price transparency in a two-sided market where hosts and guests interact, and hosts cannot independently choose to obfuscate add-on fees (e.g., cleaning fees). Instead, whether these fees are shrouded or unshrouded depends on the platform owner's design choices. We find that, even with shrouded fees, many hosts do not impose a cleaning fee, resulting in fully transparent total pricing. To examine how hosts respond to changes in price transparency, we leverage a unique natural experiment: Airbnb's shift to upfront fee disclosure for consumers from the EU following European regulatory pressures.

We find that Airbnb's price transparency led to a decrease in cleaning fees among hosts who are particularly strongly exposed to EU travelers. We also show that some hosts, those with no or low cleaning fees, charge higher prices after the policy, suggesting that they have become more aware of competitors' prices.

Although we are the first to systematically identify this effect, anecdotal evidence of similar mechanisms exists in other markets. For example, some economists believe that recent initiatives to make US hospital procedure insurance prices more transparent risk increasing prices, as transparency may deter insurers from offering hospital-specific discounts that would otherwise remain hidden.[25] Interestingly, we find that in our setting, due to the peculiarity of a peer-to-peer market where non-professional hosts are present, the price increase led to lower revenues.

For policymakers, these insights highlight the importance of considering both consumer welfare and the nuanced price-setting behaviors of sellers when regulating price transparency, as well as the fact that price obfuscation can occur on the host side. Such obfuscation can lead to inefficiently lower prices, as hosts are also unable to observe the prices of competitors. Future policies aimed at increasing consumer welfare may need to differentiate between peer-to-peer and centrally controlled platforms to account for these varied responses. On the managerial side, our analysis shows that price transparency may result in lower bookings and revenues in peer-to-peer markets – not due to lower fees, but due to some hosts increasing prices, which results in lower bookings.

[25] For more information, see: https://www.benefitspro.com/2024/07/04/health-care-price-transparency-tools-increase-prices-economists-report (last accessed: December 4, 2024).

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Appendix

A Data Matching and Imputation of Missing Cleaning Fees

Our price and booking data come from AirDNA and are available on a daily basis. Our cleaning fee data are from InsideAirbnb at a monthly frequency. To match these data sets, we first match each daily Airdna observation to the closest date for which we have an InsideAirbnb data scrape (restricting the number of days between the observation and the matched InsideAirbnb scrape to a maximum of 30 days). Next, we aggregate the data to months based on the matched InsideAirbnb date.

There are several reasons why a cleaning fee can be missing after this matching and aggregation procedure. First, even if we have InsideAirbnb data, we may be unable to match a listing we observe in the AirDNA data to the corresponding month in the InsideAirbnb data. Second, even if we can match a listing to a close enough InsideAirbnb scrape, the cleaning fee is missing for many listings in the InsideAirbnb data.

Therefore, we propose several corrections to deal with these issues. First, we only include months in which we observe any InsideAirbnb data.[26] Second, for listings for which we sometimes observe a cleaning fee and at other times it is missing, we do the following imputations: If the cleaning fee is missing for a listing in some months, but we observe the cleaning fee for months before and after this missing period, and if the cleaning fee is the same before and after the missing period, we impute the missing period with the value of the before and after periods. If we observe a cleaning fee for a listing in some months and it never changes, then we impute the missing months with the value from the observed months. Note that it is only a minor share of listings for which the cleaning fee is missing in some months while it is observed in others. For most listings, we either always observe a cleaning fee or never. Therefore, the third type of imputation is arguably the most relevant in this setting. For listings for which we never observe a cleaning fee in the InsideAirbnb data, we impute a cleaning fee of zero. Figure A1 shows the distribution of the share of observations for each listing for which we observe a cleaning fee. The figure shows that in all cities, for any given listing, we either always observe a cleaning fee or never.

When we compare some observable characteristics between listings for which we never observe a cleaning fee to those for which we always observe one in Table A1, it seems like the ones for which we do observe a cleaning fee are more professional: They charge higher prices, have more reviews, are more likely to be instant bookable as well as hosted by Superhosts and hosts with multiple listings, are booked more fre-

[26]This restriction is only relevant for the additional results using data from Rome. London and Paris both have full monthly coverage by Insideairbnb in 2018 and 2019.

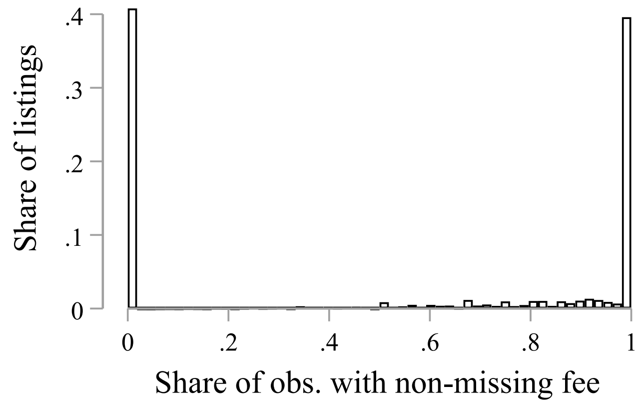


Figure A1. Share of observations with non-missing cleaning fee by listing

Table A1. Balance tables between listings for which we never observe a cleaning fees and the rest

	0% obs. fees			100% obs. fees			
London	N	Mean	SD	N	Mean	SD	Diff
Price (USD)	627,309	86.49	188.24	1,468,726	119.68	184.39	33.185***
Reviews	627,309	10.42	31.13	1,468,726	15.66	30.15	5.244***
Min. nights	627,309	3.89	25.71	1,468,726	3.62	16.75	-0.276***
Superhost	626,443	0.07	0.26	1,466,719	0.14	0.34	0.063***
Instant bookable	627,309	0.33	0.47	1,468,726	0.37	0.48	0.036***
Host listings	627,309	4.76	18.85	1,468,726	30.36	143.58	25.602***
Entire home/apt	627,309	0.32	0.47	1,468,726	0.65	0.48	0.326***
Price (USD, booked only)	232,551	108.70	129.35	617,360	157.64	151.58	48.939***
Price (USD, asked only)	847,745	144.02	415.76	996,947	165.97	285.56	21.944***
EU share	891,415	0.61	0.11	1,092,114	0.58	0.11	-0.029***
Booking length	232,554	6.24	6.06	617,360	5.96	5.11	-0.279***
Booked days	892,214	4.45	11.54	1,092,336	11.12	16.31	6.668***
Bookings	892,214	1.13	3.07	1,092,336	2.84	4.25	1.708***

quently, and are more likely to be entire homes rather than private rooms. We think it is plausible that less professional hosts are more likely to not set a cleaning fee which is then not shown on the Airbnb website and appears as missing in the InsideAirbnb data.

B Appendix of Proofs

Proof of Lemma 1: Differentiating Host 1's profit with respect to P_1 and f yields

$$\begin{aligned} P_1 &= \frac{1}{2b}(a+dP_2) - \frac{1+\lambda}{2}\cdot\frac{f}{\overline{n}}, \\ f &= \frac{1}{\overline{\eta}}\left[\frac{1}{2b\lambda}(a+dP_2) - \frac{1+\lambda}{2\lambda}\cdot P_1\right], \end{aligned}$$

and the second-order conditions for maximization hold when $4\lambda\overline{\eta}\frac{1}{\overline{n}} > (1+\lambda)^2$ which we assume holds.

Differentiating Host 2's profit with respect to P_1 and f yields

$$P_2 = \frac{1}{2b}\left(a + dP_1 + Sd\frac{f}{\overline{n}}\right),$$

and the second-order conditions for profit maximization always holds.

Proof of Proposition 1: If $d=0$, then we have that P_1^* and f^* are given by

$$\begin{aligned} P_1 &= \frac{a}{2b} - \frac{1+\lambda}{2}\cdot\frac{f}{\overline{n}}, \\ f &= \frac{1}{\overline{\eta}}\left[\frac{a}{2b\lambda} - \frac{1+\lambda}{2\lambda}\cdot P_1\right], \end{aligned}$$

which yields

$$\begin{aligned} P_1^* &= \frac{a}{2b}\cdot\frac{4\lambda\overline{\eta}\overline{n} - 2(1+\lambda)}{4\lambda\overline{\eta}\overline{n} - (1+\lambda)^2}, \\ f^* &= \frac{a\overline{n}(1-\lambda)}{4\lambda\overline{\eta}\overline{n} - (1+\lambda)^2}b. \end{aligned}$$

Note that the second-order condition derived in the proof above, $4\lambda\overline{\eta}\frac{1}{\overline{n}} > (1+\lambda)^2$, imply that $4\lambda\overline{\eta} > \overline{n}(1+\lambda)^2 > \frac{1}{\overline{n}}(1+\lambda)^2$ since $\overline{n} > 1$ so that f^* is indeed positive.

Differentiating each with respect to λ implies that it is straightforward to check that $\frac{dP_1^*}{d\lambda} > 0$, but $\frac{df^*}{d\lambda} < 0$ if and only if $4\overline{\eta}\overline{n} > (1+\lambda)(3-\lambda)$ but $4\lambda\overline{\eta}\overline{n} > (1+\lambda)^2$ implies that this holds if $\frac{(1+\lambda)^2}{\lambda} > (1+\lambda)(3-\lambda)$ which always holds.

Proof of Proposition 2: Differentiated the P_2 best response function in Lemma 1with respect to S yields a clear increase in P_2 which generates in indirect increase in P_1 and f based on the best response functions in Lemma 1.

C The Effect on Booked Cleaning Fees

These results correspond to the ones reported in Section 4 except that we use the booked cleaning fee rather than the asked cleaning fee. Table C1 presents the DiD estimates. The effect of the price transparency on the cleaning fee is qualitatively similar to the one in the main analysis. Figure C1 presents the event study analysis and shows that the effect of the policy is significant and negative. Moreover, also in this case, it seems that there are some anticipation effects just after Airbnb commits to fully complaying with European regulators' demands. This can be due to anticipation by hosts or due to platform design experiments on Airbnb that affected a subset of hosts.

Table C1. DiD for booked cleaning fees

London	(1)	(2)	(3)	(4)
Post-policy (α)	0.422***	1.858***	1.878***	1.896***
	(0.0476)	(0.0581)	(0.0597)	(0.0617)
Post-policy X High EU (β)	-0.558***	-0.558***	-0.599***	-0.622***
	(0.0686)	(0.0686)	(0.0724)	(0.0761)
Linear time trend	0.120***	0	0	0
	(0.00331)	(.)	(.)	(.)
Constant	27.45***	32.53***	32.53***	32.53***
	(0.155)	(0.0194)	(0.0194)	(0.0197)
Listing FEs	✓	✓	✓	✓
Month FE		✓	✓	✓
Large geo-month FEs			✓	
Small geo-month FEs				✓
Adj. R^2	0.99	0.99	0.99	0.98
Avg. cleaning fee	33.34	33.34	33.34	33.34
Obs.	1,021,866	1,021,866	1,021,866	1,021,806

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

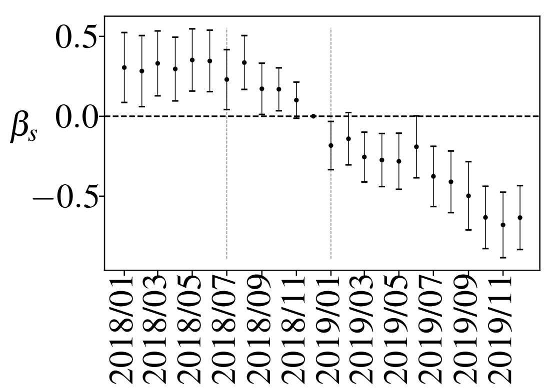


Figure C1. Event study analysis for the booked cleaning fee. The regressions include listing as well as geography-month fixed effects. Standard errors are clustered on the listing level.

D Price analysis: Minimum nights of one

This section presents the results of an analysis similar to that in Section 5, but with the sample restricted to listings that require a minimum stay of only one night. Under this restriction, we do not adjust the cleaning fee when calculating the total price, thereby analyzing total prices applicable exclusively to one-night stays. Apart from these modifications, the calculation of δ_i follows the approach outlined in Section 5.

Figure D1 displays the resulting δ_is for the estimation sample, as well as for listings that never impose a cleaning fee. The observed patterns are consistent with those in Figure 5. Specifically, for the entire sample, the distribution of δ_i remains centered around zero, while for listings without a cleaning fee, δ_i generally skews positive.

Once again, we define as "more affordable" listing all those listings whose δ_i is above the 75th percentile (9). "Less affordable" listings are those whose δ_i is below the 25th percentile (-6.7). Figure D2 reports the average prices (both excluding and including the cleaning fee) over time for "more affordable" and "less affordable" listings. The figure shows that prior to the policy change, net prices of "more affordable" and "less affordable" listings behave very similarly and start to diverge after the policy change. In particular, "more affordable" listings become more expensive in terms of net prices after the policy change. However, accounting for the fee reveals that the total price was generally lower for "more affordable" listings before the policy change but began to converge after the policy change.

In Table D1, we report the DiD results showing how the prices of "more affordable" listings changed compared to those of other listings after the policy change. The results are qualitatively in line with those reported in Table 3. The event study results shown in Figure D3 show that conditional pre-trends seem to develop in parallel and that prices of "more affordable" listings indeed increased after the policy change.

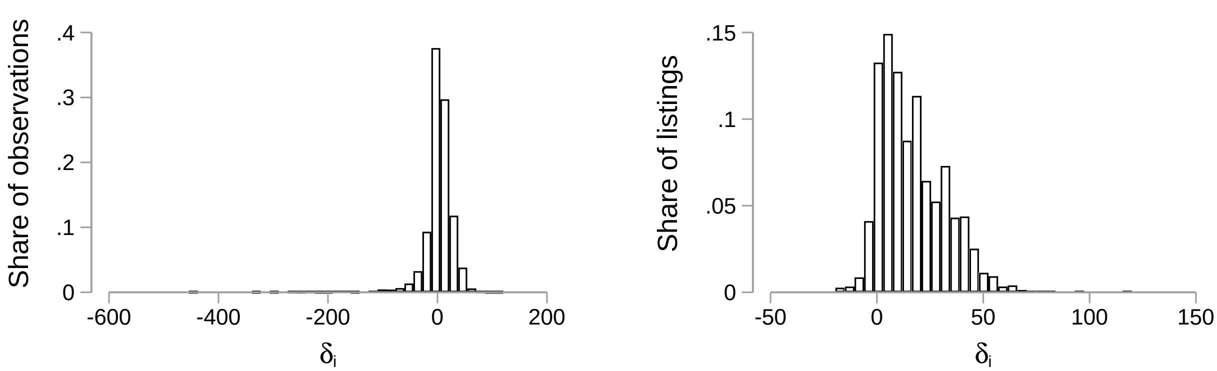


Figure D1. Distribution of δ_i for all listings (left) and for zero fees only (right)

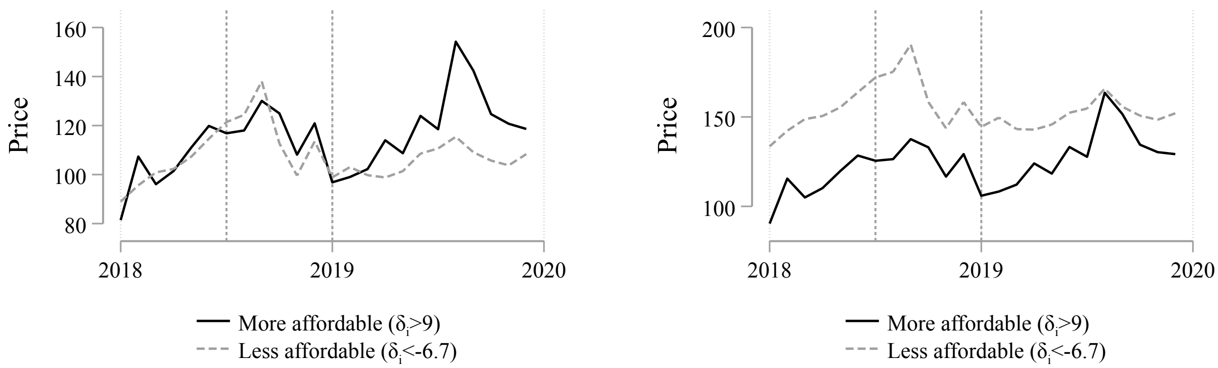


Figure D2. Prices net of fee (left) and including fee (right) over time by high and low δ_i

Table D1. Difference-in-differences results for prices

	Outcome: Price net of fee				Outcome: Price including fee			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-policy (α)	-11.83***	2.307***	2.267***	2.364***	-11.96***	3.321***	3.281***	3.387***
	(0.893)	(0.374)	(0.375)	(0.417)	(0.893)	(0.378)	(0.380)	(0.422)
Post-policy X "More affordable"	5.876***	5.862***	6.221***	6.546***	5.924***	5.911***	6.274***	6.600***
	(1.141)	(1.140)	(1.142)	(1.166)	(1.147)	(1.145)	(1.147)	(1.174)
Linear time trend	1.177***	0	0	0	1.273***	0	0	0
	(0.0771)	(.)	(.)	(.)	(0.0772)	(.)	(.)	(.)
Constant	37.36***	87.47***	87.39***	87.25***	54.78***	109.0***	108.9***	108.7***
	(3.365)	(0.327)	(0.332)	(0.337)	(3.372)	(0.329)	(0.334)	(0.339)
Listing FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FE		✓	✓	✓		✓	✓	✓
Large geo-month FEs			✓				✓	
Small geo-month FEs				✓				✓
Adj. R^2	0.66	0.66	0.66	0.61	0.69	0.69	0.69	0.64
Avg. total price	90.36	90.36	90.36	90.36	112.40	112.40	112.40	112.40
Obs.	211,627	211,627	211,627	211,627	211,627	211,627	211,627	

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

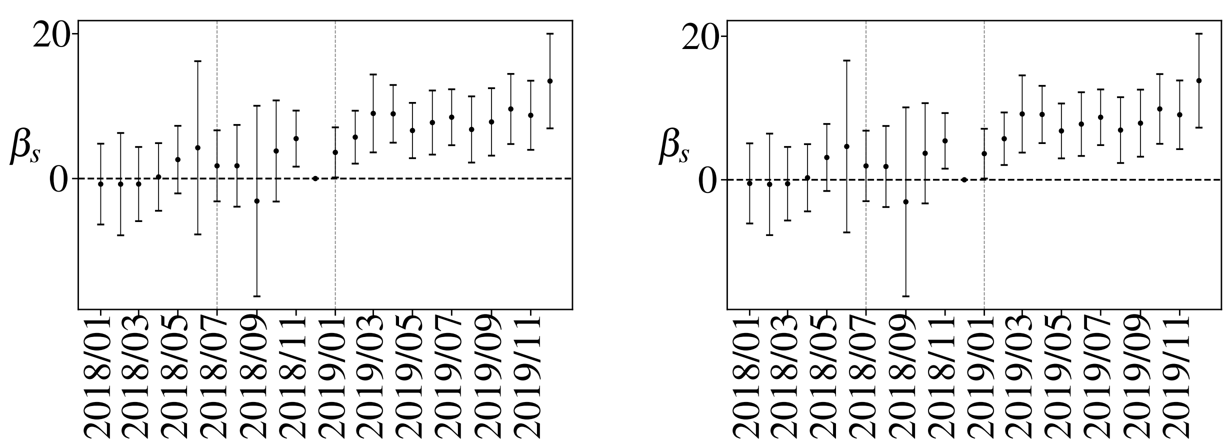


Figure D3. Event study for asked prices net of fees (left) and including fee (right). Includes linear time trend and listing as well as geographic area-month FEs. Standard errors clustered on listing level. Bars show 95% confidence intervals.

E Price Frictions

We now further examine various factors that may influence the pricing on Airbnb and, consequently, our results. Huang (2022) shows that hosts on Airbnb encounter pricing frictions, leading to suboptimal pricing; notably, they do not adjust prices as frequently as would be optimal. Furthermore, Li et al. (2022) suggests that many Airbnb hosts are non-professionals who are unresponsive to demand shocks. We have already seen that Superhosts tend to be more responsive to the policy on what concerns the cleaning fee. If a substantial number of hosts fail to respond to platform changes, we would not detect any supply-side reactions to the policy change. On the other hand, Airbnb provides a pricing algorithm that hosts can choose to utilize. Frequent price adjustments may indicate the use of such pricing algorithms. If a significant number of hosts rely on the smart pricing tool, we would not expect them to respond to the policy change in line with our model, as the tool likely incorporates the fully inclusive price even prior to the implementation of full transparency.

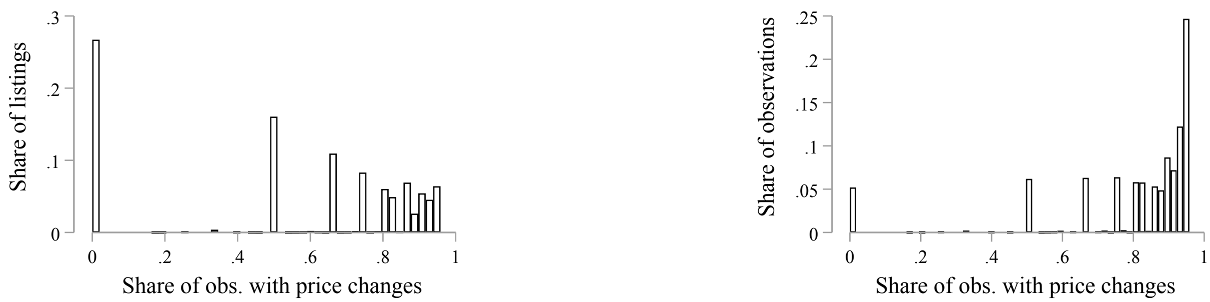


Figure E1. Distribution of share of observations with price changes, by listing. Each listing is either represented only once (left) or weighted by its number of observations (right).

In what follows, we examine the frequency of price adjustments among Airbnb listings. The left panel of Figure E1 shows the distribution of the share of observations for each listing for which we observe a price change from one period to the next. There is a substantial group of listings for which we never observe any price changes. However, many of these listings appear in the data only once, making up a small share of overall observations, as shown in the right panel of Figure E1. Moreover, we also observe a substantial share of listings which change their prices in almost every period in which we observe them. This behavior could be indicative of use of smart pricing. However, these high-frequency changers make up less than 10% of listings suggesting our supply-side results are likely driven by the behavior of host actions.

F Rome and Paris

In this section, we conduct robustness checks on our findings by examining the next two largest European cities by number of listings: Paris and Rome. However, these cities present certain data quality issues that may impact our identification strategy. First, in the case of Paris, a concurrent tax policy change likely attenuates the observed effects. Specifically, a new tourist tax was introduced in January 2019, ranging from €0.65 (for 1- and 2-star campsites) to €14.95 (for luxury hotels) per person, per night.[27] Given that the tax burden is shared by hosts and travelers (Bibler et al. (2021)), we expect this to decrease listing prices and, if anything, decrease cleaning fees. This could explain why we find little to no price effect for Paris relative to the results in London. Second, for Rome, we lack InsideAirbnb data for the period prior to April 2018. As a result, our analysis for Rome begins in April 2018 rather than January 2018, making the pre-policy period shorter than in the main analysis. In addition, Rome, and Italy more generally, does not have within city jurisdictions which limits our ability to meaningfully control for neighborhood level fixed effects (we describe this issue in greater detail below).

Despite these limitations, we find that our main result – the impact of Airbnb's design change on the cleaning fee – remains consistent across cities. However, the effect on prices is noisier for Rome and absent for Paris. We also offer possible explanations for these price effects, though we cannot rule out that they may be influenced by the identified data quality issues.

The effect on cleaning fees Table F1 presents the main results from the DiD estimation for Rome and Paris using the asked cleaning fee. Columns (1) to (4) present results for Paris, where the average cleaning fee is approximately 35 EUR, while columns (5) to (8) present results for Rome, where the average cleaning fee is 25 EUR. In columns (1) and (5), we show results in the presence of a linear time trend. In columns (2) and (6), month fixed effects are added, whereas in columns (3), (4), (7), and (8), we include geography-month fixed effects. The coefficient of interest is *Post-policy* $\times$ *High EU*, which gives the average treatment effect for a listing with above-median exposure to EU travelers compared to a listing with below-median EU exposure. On average, the introduction of fee transparency results in a reduction in the cleaning fee of about 0.9 EUR in Paris and 0.7 EUR in Rome. Compared to the average cleaning fee, these reductions amount to approximately three percent. The event study coefficients reported in Figure F1 show that conditional pre-trends seem to develop fairly parallelly and that the drop in cleaning fees begins in January 2019.

[27] For more information, see: `https://parisjetaime.com/eng/article/tourist-tax-a616` (last accessed: December 13, 2024).

Table F1. DiD for asked cleaning fees in Paris and Rome

	Paris				Rome			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-policy	0.476***	2.458***	2.473***	2.483***	0.0804	1.391***	1.434***	1.434***
	(0.0898)	(0.105)	(0.107)	(0.109)	(0.0693)	(0.0813)	(0.0853)	(0.0853)
Post-policy X High EU	-0.837***	-0.836***	-0.869***	-0.888***	-0.601***	-0.601***	-0.701***	-0.701***
	(0.119)	(0.119)	(0.125)	(0.129)	(0.0936)	(0.0936)	(0.105)	(0.105)
Linear time trend	0.165***	0	0	0	0.108***	0	0	0
	(0.00519)	(.)	(.)	(.)	(0.00463)	(.)	(.)	(.)
Constant	27.08***	34.10***	34.10***	34.10***	20.08***	24.74***	24.74***	24.74***
	(0.241)	(0.0313)	(0.0312)	(0.0314)	(0.222)	(0.0323)	(0.0324)	(0.0324)
Listing FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FE		✓	✓	✓		✓	✓	✓
Large geo-month FEs			✓				✓	
Small geo-month FEs				✓				✓
Adj. R^2	0.98	0.98	0.98	0.98	0.96	0.96	0.96	0.96
Avg. cleaning fee	35.08	35.08	35.08	35.08	25.39	25.39	25.39	25.39
Obs.	584226	584226	584226	584226	439819	439819	439819	439819

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.

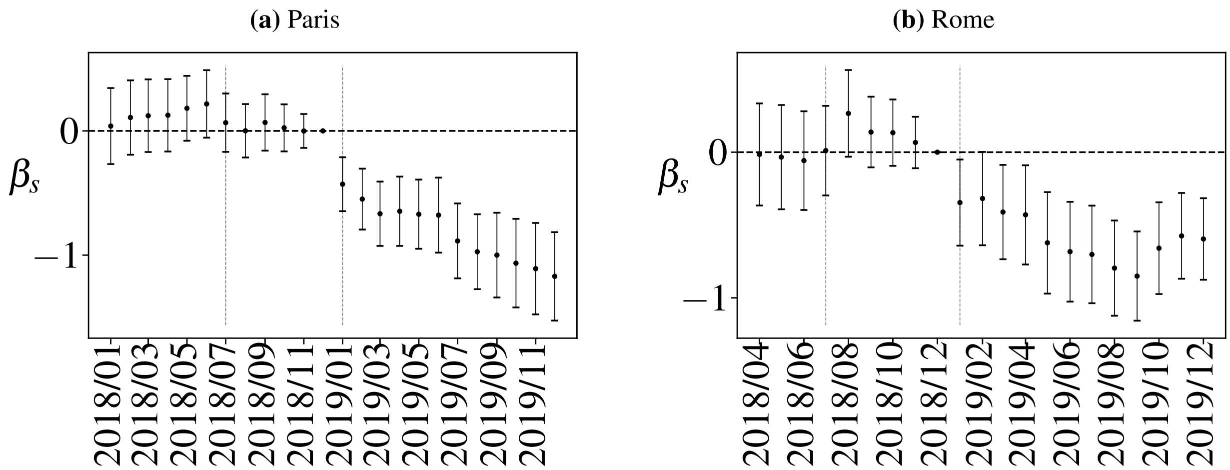


Figure F1. Event study analysis for the asked cleaning fee. The regressions include listing as well as geography-month fixed effects. Standard errors are clustered on the listing level. Bars show 95% confidence intervals.

The effect on prices. We now focus on the effect of price transparency on the nightly price set by the hosts. As described in Section 5, we calculate δ_i which measures how affordable a listing appears if the fee is included compared to if it is not. Figure F2 shows the distribution of δ_i in Paris and Rome for the entire sample, whereas Figure F3 restricts attention to those listings with a zero cleaning fee. Similarly as in London, those listings without a cleaning fee tend to have a positive δ_i which implies that they appear more affordable if the total price is compared as opposed to only the base price.

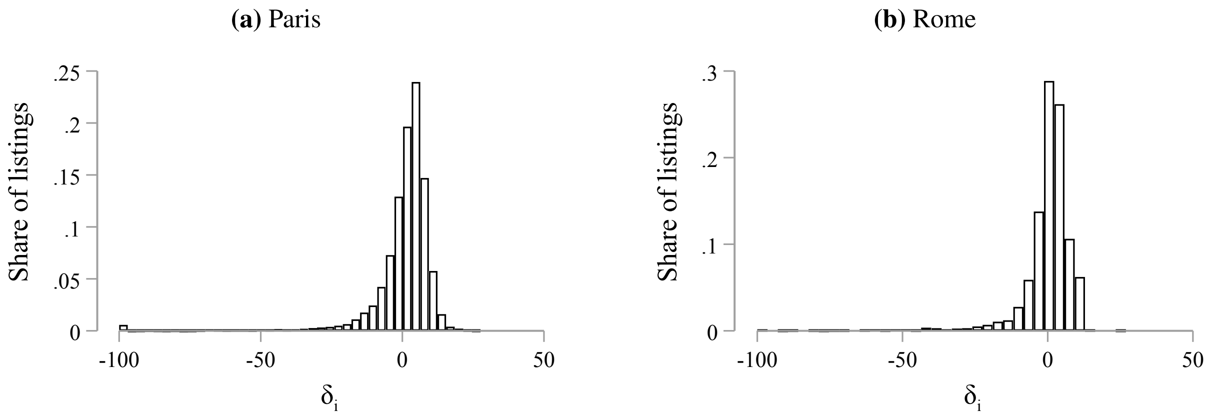


Figure F2. Distribution of δ_i for entire sample. Values are windsorized at -100 and 40 for better readability.

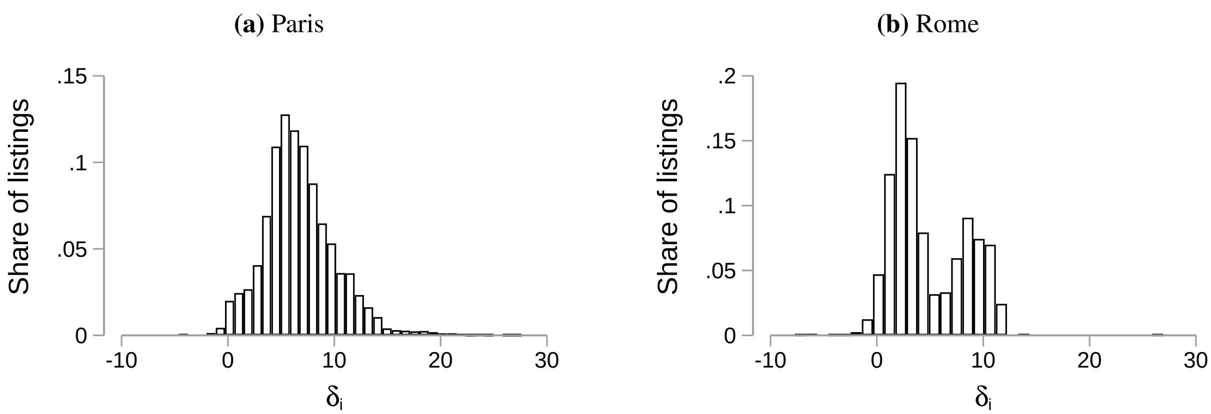


Figure F3. Distribution of δ_i for zero-fee listings only

Again, we next define "more affordable" listings as those whose δ_i is larger than the 75th percentile. "Less affordable" listings are those whose δ_i is smaller than the 25th percentile. Figure F4 shows the average price (net of fees) over time for these two groups in both cities. Figure F5 shows the same for the total price including the fee.

Table F2 presents the results of the DiD analyzes that compare "more affordable" listings with the rest. Contrary to the case of London, there is no effect on prices in Paris. We do find an effect that is significant and positive for Rome. However, the estimates are noisy and the magnitude of the main effects smaller than for London. We also present event studies in Figure F6, which illustrate the price dynamics before and after the shock in both Paris and Rome. As observed, the effect appears to be quite noisy.

Both of these cities have their own data quality issues as previously discussed (e.g., a concurrent tax change in Paris that directly affects prices). These issues may have contributed to the more noisy results in

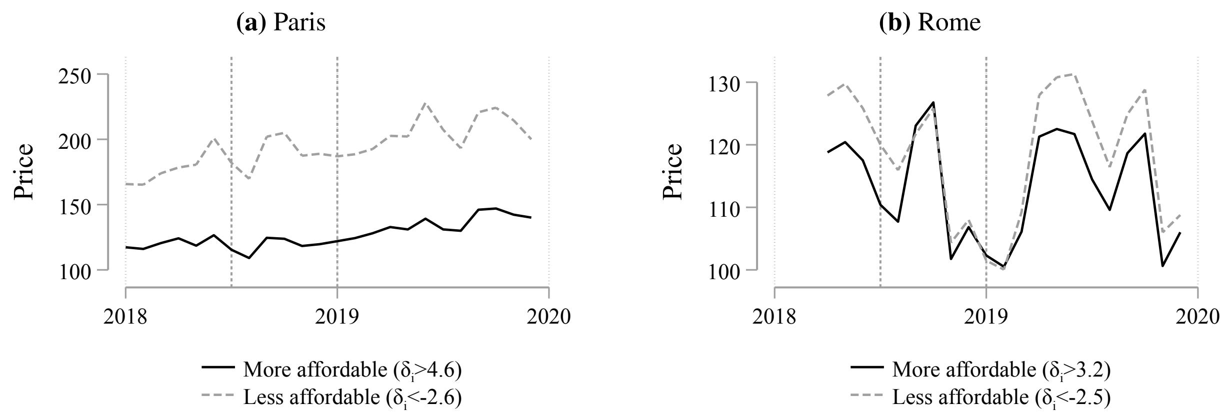


Figure F4. Prices (net of fee) over time by δ_i

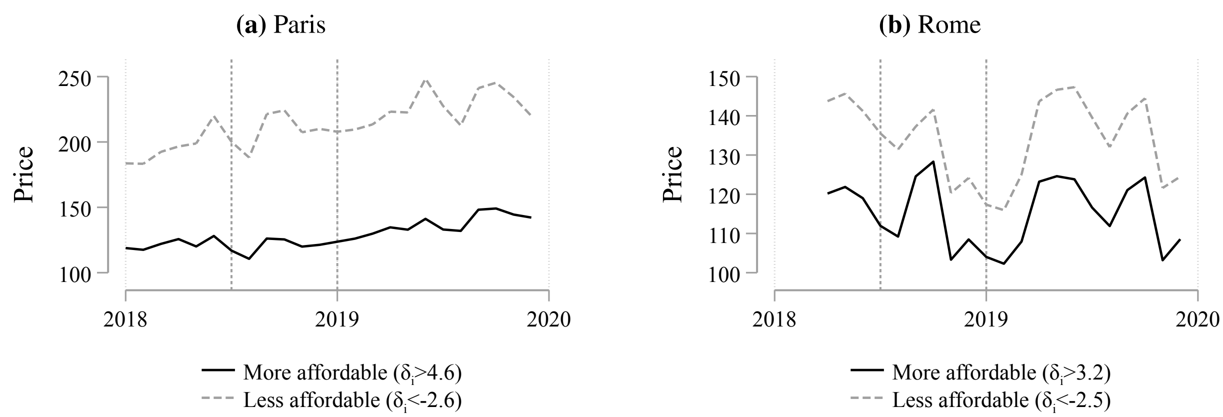
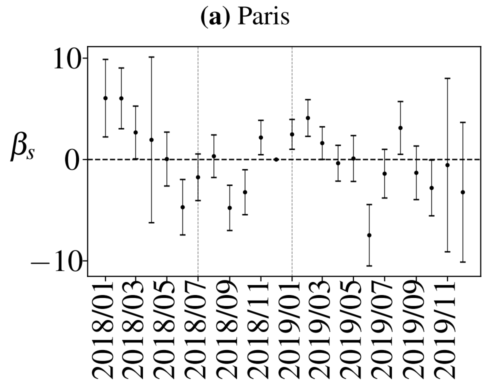


Figure F5. Prices (including fee) over time by δ_i

Table F2. DiD for total prices (including fee)

	Paris				Rome			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-policy	-5.394***	9.143***	9.084***	9.029***	-1.241*	2.861***	2.803***	2.803***
	(0.518)	(0.547)	(0.550)	(0.508)	(0.553)	(0.410)	(0.418)	(0.418)
Post-policy X More affordable	-0.209	-0.217	-0.0590	0.117	0.889	0.905	1.294*	1.294*
	(0.880)	(0.879)	(0.887)	(0.894)	(0.623)	(0.622)	(0.640)	(0.640)
Linear time trend	1.218***	0	0	0	0.0927	0	0	0
	(0.0547)	(.)	(.)	(.)	(0.0586)	(.)	(.)	(.)
Constant	83.10***	134.6***	134.6***	134.6***	99.48***	101.9***	101.8***	101.8***
	(2.448)	(0.182)	(0.182)	(0.171)	(2.652)	(0.192)	(0.194)	(0.194)
Listing FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FE		✓	✓	✓		✓	✓	✓
Large geo-month FEs			✓				✓	
Small geo-month FEs				✓				✓
Adj. R^2	0.70	0.70	0.70	0.70	0.85	0.85	0.85	0.85
Avg. total price	138.07	138.07	138.07	138.08	103.52	103.52	103.52	103.52
Obs.	494,010	494,010	494,007	493,969	393,014	393,014	392,945	392,945

Notes: Standard errors clustered on the listing level. ***, **, * indicate statistical significance at the five, one, and 0.1 percent level, respectively.



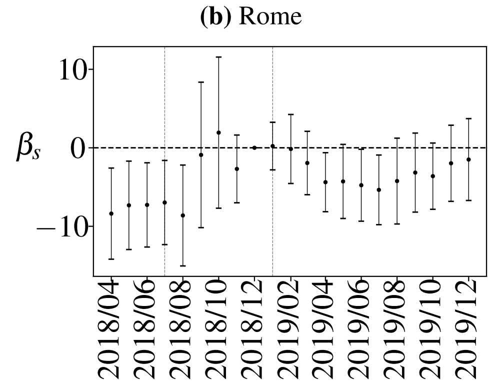


Figure F6. Event study for the asked total price (including the cleaning fee). Includes linear time trend and listing as well as geographic area-month FEs. Standard errors clustered on listing level. Bars show 95% confidence intervals.

Rome and Paris. We next explore possible alternative explanations for why we do not see as clear a price effect as in London.

Figure F7 shows the distribution of the share of observations per listing in which a price change occurs compared to the previous period. These distributions differ noticeably between the two cities. In Paris, a significant share of observations (over 10 percent) correspond to hosts who never adjust their prices over time. Although it is difficult to determine why their prices remain constant over time, previous studies suggest that this behavior may stem from cognitive constraints or the non-professional nature of some hosts(Huang, 2022). Importantly, if a significant share of listings never adjust their prices, it becomes more challenging to detect any impact of the policy change on pricing. Additionally, this lack of adjustment dampens potential second-order effects, where some hosts might react to others raising their prices in response to the policy change.

In sharp contrast, approximately 40 percent of listings in Rome adjust their prices in every observed period. This behavior aligns with the use of smart pricing algorithms, which dynamically set prices based on demand and may, therefore, dampen or offset hosts' immediate upward pricing responses. At the very least, these frequent price adjustments introduce significant noise into the data, which could explain the higher variability in the estimates for Rome. Despite this, we still find evidence of a price increase following the policy change, qualitatively consistent with the results observed in London.

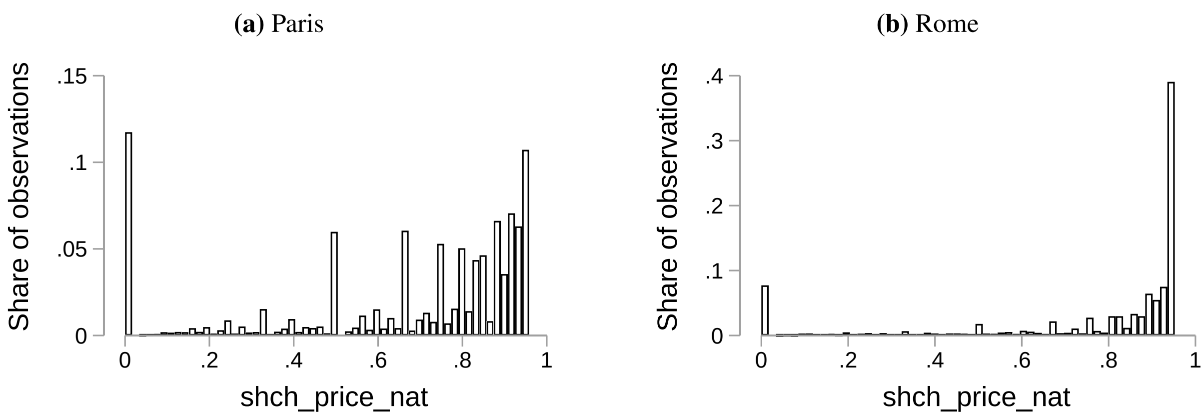


Figure F7. Distribution of share of observations with price changes, by listing. Each listing is weighted by its number of observations.

G Derivation of revenue impact decomposition

Plugging $rev = Q(nP + f)$ into Equation 3 and rearranging yields:

$$\begin{aligned}
\Delta rev &= Q'(n'P' + f') - Q(nP + f) \\
&= Q'(n'P' + f') - Q(nP + f) + Q(n'P' + f') - Q(n'P' + f') \\
&= (Q' - Q)(n'P' + f') + Q(n'P' - nP + f' - f) \\
&= \Delta Q(n'P' + f') + Q(n'P' - nP + \Delta f) + Q'(n'P' - nP + \Delta f) - Q'(n'P' - nP + \Delta f) \\
&= \Delta Q(n'P' + f') + Q'(n'P' - nP + \Delta f) - (Q' - Q)(n'P' - nP + \Delta f) \\
&= \Delta Q(n'P' + f') + Q'(n'P' - nP + \Delta f) - \Delta Q(n'P' - nP + \Delta f)\,.
\end{aligned} \tag{6}$$

Note that

$$\begin{aligned}
n'P' - nP + \Delta f &= n'P' - nP + \Delta f - n'P + n'P \\
&= n'(P' - P) + (n' - n)P + \Delta f \\
&= n'\Delta P + \Delta nP + \Delta f \\
&= n'\Delta P + \Delta nP + \Delta f - \Delta nP' + \Delta nP' \\
&= n'\Delta P + \Delta nP' - \Delta n(P' - P) + \Delta f \\
&= n'\Delta P + \Delta nP' - \Delta n\Delta P + \Delta f\,.
\end{aligned} \tag{7}$$

Plugging that back into Equation (6) and rearranging yields

$$\Delta rev = \Delta Q(n'P' + f') + (Q' - \Delta Q)(n'\Delta P + \Delta nP' - \Delta n\Delta P + \Delta f)\,. \tag{8}$$

H Event studies for equilibrium outcomes

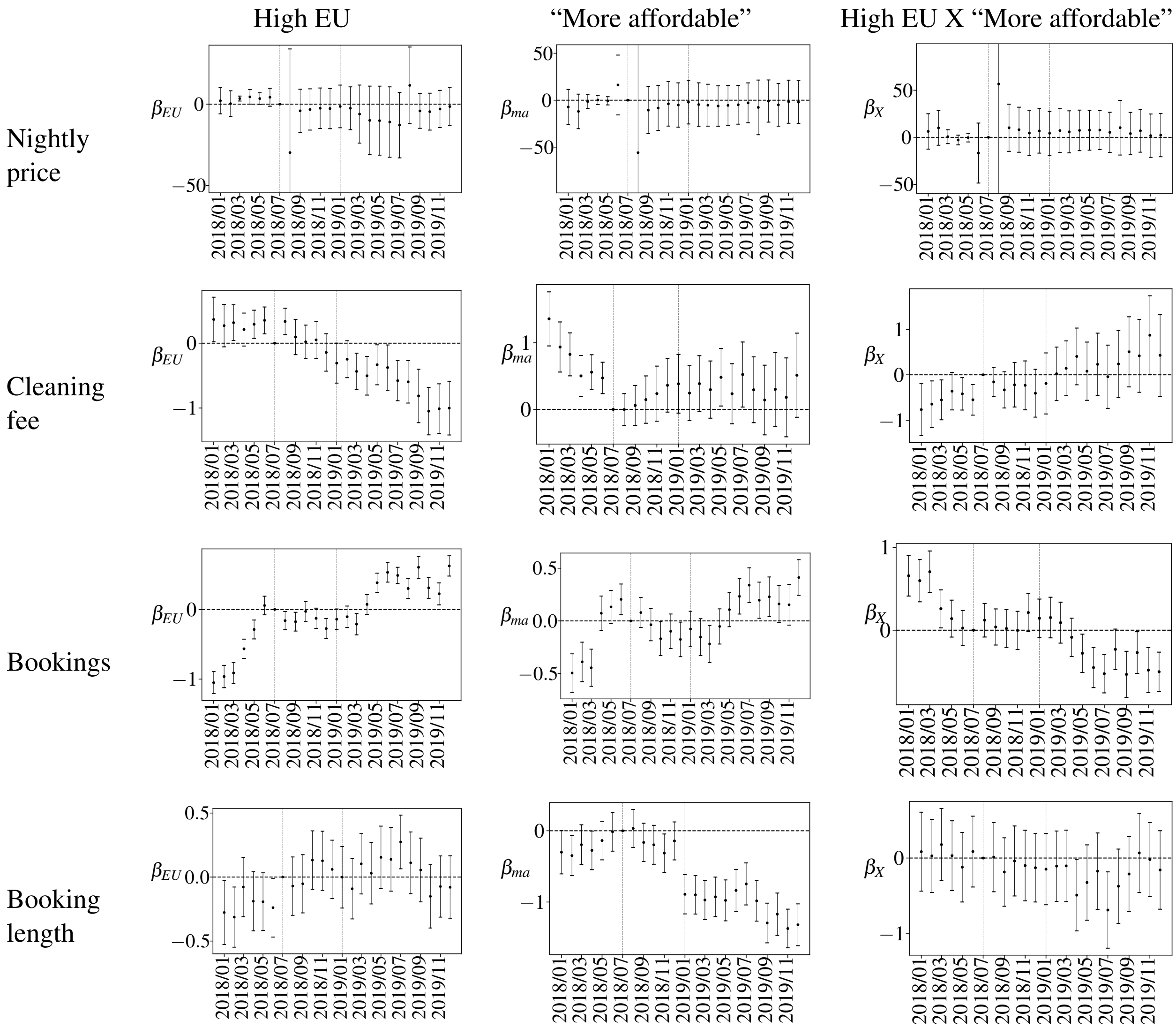


Figure H1. Event study results corresponding to Table 7. Includes linear time trend and listing as well as geographic area-month FEs. Standard errors clustered on listing level. Bars show 95% confidence intervals.