Price Discrimination 2.0: Opaque Bookings in the Hotel Industry*

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Abstract

The emergence of opaque selling (i.e., when a product characteristic is only revealed to the customer after payment) has motivated a growing theoretical literature but little progress on the empirical front. This paper tries to fill this gap. We document the main features of opaque selling using a unique dataset from the lodging industry that includes bookings made in opaque platforms—Priceline and Hotwire—matched to their equivalent booking in the transparent market. We argue that opaque platforms allow hotels to achieve demand segmentation across-channels instead of using within-channel intertemporal price discrimination strategies. Opaque discounts relative to a transparent booking vary across selling channels and hotel quality segments. Consistent with consumer self-selection based on transaction costs and dispersion of preferences over transparent products, the average opaque discounts 40% in the posted-price platform and 49% in the auction-based platform. We find weak evidence of price-skimming strategies traditionally associated to revenue management practices in the travel industry. Moreover, we reject the hypothesis that hotels use opaque selling as a last-minute resource to dispose unsold inventory.

JEL Codes: D43, D47, L11, M31.

Keywords: Two-sided markets, Opaque platforms, Price discrimination, Lodging Industry, Hotwire, Priceline.

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1 Introduction

The diffusion of e-commerce has produced shakeouts in nearly all retail industries. As consumers shifted their offline purchases to the internet, markets experienced entry by new players simultaneously with exit and repositioning of incumbent firms. The travel agency industry is a case in point of this transformation. The rise in online bookings and the evolution in IT reshaped the sources of competitive advantages and led to the replacement of small and local brick-and-mortar agencies by large and global online travel agencies (OTAs).[1] More important to us, the change in the market structure of the travel industry allowed for disruptive innovations in business processes like the introduction of opaque selling by OTAs. Although still incipient, different opaque selling mechanisms are currently implemented by most OTAs accounting for a quarter of hotels' transient room-nights bookings (HSMAI Foundation, 2012). Moreover the large margins captured by opaque intermediaries suggests a promising future for this new selling channel in other industries.[2] The goal of this paper is to contribute to our understanding of opaque selling using transaction-level data from the lodging industry.

Opaque platforms offer online travel booking services (hotel, rental car and airline bookings) concealing the provider's identity from buyers until the transaction is completed. An advantage, highlighted in the industry, is that it allows service providers to target price-sensitive customers with lower prices while avoiding the negative effects associated with traditional markdowns. A disadvantage however is that, since product differentiation becomes immaterial, competition to supply the opaque platform is fierce (reverse auction) and lowers sellers' margins in the opaque *and* possibly transparent markets. This latter point has generated heated industry debate and motivated theoretical work on the strategic benefits of opaque selling (Fay, 2008; Shapiro and Shi, 2008; Jerath et al., 2010; Tappata, 2011).[3] Tough these theories emphasize the screening properties of opaque selling, their predictions differ on whether the opaque channel is used to sell distressed inventory in the last minute or as a static price discrimination device. The richness of our data allows us to exploit the variation in the timing of advance-bookings to examine the merits of each hypothesis.

[1] See Goldmanis et al. (2010) for a quantitative analysis of the 1994-2003 market structure evolution in this industry.

[2] For example, `Scorebig.com` uses opaque selling of seats at live concerts and sporting events.

[3] As the CEO of Delta Airlines, Leo Mullin, said after Delta joined Priceline's platform: "There was great suspicion that this would lead to excessive discounting. How would it threaten Delta? We had very strong arguments. The general tenor was definitely against it." (*The E Gang*, Forbes; July 24^{th}, 2000).

Understandably, opaque products are sometimes called probabilistic goods. They represent a lottery over a set of traditional or transparent products and are therefore viewed as inferior by any risk-neutral or risk-averse buyer. It is for this reason that, all else equal, opaque bookings are cheaper than transparent bookings and appeal to consumers with low dispersion of preferences over the available—transparent—alternatives. In addition, consumers can self-select among opaque platforms based on the nature of the transaction mechanism used (auction-based or posted prices) and the amount of information suppressed by the intermediary (opacity level). The magnitude of the price discounts required to compensate buyers of opaque products for bearing the associated risks and transaction cost is an empirical question that we tackle in this paper. Consumers in our sample require an unconditional 44 percent discount to make an opaque booking. We document how these large discounts vary across transaction mechanisms, opacity level, quality and other explanatory variables relevant to the lodging industry.

To the best of our knowledge, this is the first paper that studies the empirical properties of opaque selling using transacted prices. We use a large dataset with opaque and transparent hotel-room bookings in eighteen cities in North America from October 2011 to June 2012. There are two salient features of our data that make the analysis unique. First, we observe the hotel identity in each opaque transaction and can therefore compare the opaque and transparent rates controlling for the exact same service provider and booking features (e.g., check-in and booking dates).[4] Second, we use data from the two largest opaque platforms—Priceline and Hotwire—that differ in their selling format.[5] More specifically, the data include successful bids on Priceline's Name Your Own Price system (NYOP) and bookings made on Hotwire's Secret Hot Rates (SHR).[6] The two platforms differ in the way buyers and the seller interact as well as the amount of information disclosed to the buyers by the platform. The following example helps to clarify these differences. Imagine a customer attempting to book a hotel room on a given city-area (e.g., Downtown Los Angeles) and date.

[4] Courty and Liu (2013) and Fay and Laran (2009) are the only two studies that employ opaque prices. In both cases, small samples of Hotwire's posted prices are used. Since these data do not contain the hotel identity associated to each opaque rate its use is limited to inferences on availability and price volatility over time in this specific opaque channel.

[5] Priceline and Hotwire are the opaque selling pioneers. They introduced their systems in 1999 and 2000 respectively. Although offerings by opaque competitors have increased in recent years (Expedia and Travelocity launched opaque selling channels in 2011), they are the clear dominant players in the industry ("Opaque Selling in 2011" Hotel Yearbook 2011, p.96-98).

[6] Priceline.com has traditionally offered users the option to book in their transparent site or through the opaque NYOP system. More recently, Priceline added the "Express Deals" system which is similar to Hotwire's (i.e., posted prices). We only have data on Priceline's NYOP bookings and refer to them loosely as rooms booked on Priceline.

When using Hotwire.com, the consumer is presented with a list of hotels, one for each area–stars pair, displaying room rates and hotel amenities (e.g. parking, fitness room, free–wifi, etc). The booking process and user interface is simple and mimics that of a transparent platform like Hotels.com. The key difference however is that hotels names are hidden from the buyer and only revealed after the booking has been paid.[7]

On the other hand, a customer using Priceline.com is asked to select the desired room characteristics and enter her willingness to pay for it.[8] The room characteristics include check-in and check-out dates, city, hotel quality and opaque area.[9] Once the customer commits to the booking (i.e., credit card information is entered), Priceline procures the room by running an auction among all participating hotels that match the previously specified characteristics and notifies the customer with the booking outcome.[10] The hotel name is revealed if the transaction is successful and this happens when a secret threshold price, in principle the winning bid plus Priceline's commissions, is below the customer's named price. If the named price is below this threshold price the transaction is rejected and the customer is prompted to try again with a new bid the following day.[11]

It is important to highlight the differences in the booking mechanisms used by Hotwire and Priceline. First, while room rates are posted on Hotwire's website, buyers using Priceline actively bid for a room. In Priceline's system, the role of transaction costs, impatience, expectation formation about the platform's threshold price, and other frictions can affect consumer sorting and the equilibrium discount. Second, in some cases, Hotwire discloses additional information regarding the amenities of the hotel underlying the opaque booking. It is possible that this extra information reduces the level of opacity and therefore consumers' uncertainty. Booking opacity levels vary significantly across markets (e.g., a four-star booking is a different probabilistic good if the opaque area is Manhattan's downtown than if it is La Guardia airport). This allows us to exploit the within-platform variation in booking discounts to estimate the effects of opacity on consumers' willingness to pay and relate the variation in

[7]The nature of opaque selling requires all bookings to be non-refundable, non-changeable and non-transferable.

[8]Figures 1 and 2 in Appendix A display snapshots of Hotwire and Pricelines's user interfaces.

[9]The opaque areas used by Hotwire and Priceline are indistinguishable from each other. Figures 11–13 in Appendix B show some of Hotwire's opaque areas.

[10]Strictly speaking, Priceline and Hotwire select the hotels from their GDS (Global Distribution Systems) with hotels' schedules of rooms and rates available. Hotels can change their "wholesale" rates and inventory at any time making the process equivalent to a real-time auction.

[11]In some cases, the bidder is allowed to bid again by redefining the product category selected (i.e., the geographic area–quality pair).

discounts across platforms with the different features of the opaque selling format (posted price vs. auction).

The travel industry serves two broad and very different types of customers. On the one hand, leisure travelers are viewed as price-sensitive, with low willingness to pay for special amenities, early demand realization and flexible schedules. On the other hand, business travelers are naturally price-insensitive (i.e., company pays), have strong preferences over a particular hotel (e.g., due to meetings or loyalty programs), late demand realization and high demand uncertainty (e.g., a work-related meeting scheduled a month in advance can be canceled in the last minute). Absent the possibility of first-degree price discrimination, hotels and airlines have traditionally relied on revenue and yield management strategies to separate these consumers based on the correlation of their preferences over product attributes. For example, to minimize the cannibalization of sales to the business segment, leisure travelers have been targeted with early-booking discounts and lower weekend-rates or Saturday stay-over requirements (Talluri and Van Ryzin, 2005; Phillips, 2005).[12] One natural question we ask is whether hotels use the new opaque channels to substitute or complement these price discrimination strategies. In other words, do consumer types fully sort by choosing from the menu of channels or do hotels need to use within-platform pricing strategies to achieve finer demand segmentation? This issue has not been addressed by the existing theories of opaque selling. As we argue in Section 2, the answer depends on the underlying heterogeneity in consumers' preferences and is therefore an empirical question.

Our findings suggest that hotels effectively use the opaque channels to price discriminate consumers based on preference heterogeneity and transaction costs. Predicted opaque rates in the auction-based platform are on average 49.3% lower than in the transparent market. Notably, the discounts for posted opaque rates are about 10 percentage points lower. The fact that both systems have survived in equilibrium highlights the importance of selling format design and information suppression to further segment price-sensitive customers. Opaque discounts increase monotonically with hotels' quality in both systems. A full star increase in hotel's rating is associated with a 5 percentage point increase in the opaque discount. We relate this result

[12]These "rate feces" are based on the time of purchase and consumption. Hotels can also use physical rate fences according to room-type attributes (view, room size, bedding type), or group-based (senior and AAA member discounts) fences (Kimes, 2002). Aside from anecdotal evidence by industry experts and scholars, there is little work using pricing data that documents the use of these practices by hotels. An exception being Abrate et al. (2012) that finds evidence of inter-temporal price discrimination by hotels in Europe, a market where opaque selling is still in its infancy.

to a demand-side story since product differentiation and the dispersion of consumer valuations is expected to be larger in the higher quality segments. Interestingly, our findings indicate that opaque bookings are not used as a last-minute resource to dispose unsold inventory. Instead, the data is consistent with the static price-discrimination models in the literature (Fay, 2008; Shapiro and Shi, 2008; Tappata, 2011). Moreover, the lack of evidence of within-platform price discrimination based on check-in dates (weekends) or time of booking (early discounts) is consistent with the notion that opaque selling channels are a substitute rather than a complement to the traditional price discrimination strategies associated with the travel industry.

We also investigate the extent of selection on the supply side by matching each opaque transaction to the distribution of hotel rates in the transparent market. We find that hotels selling opaque are more likely to be those in the lower tail of the transparent price distribution. This is consistent with anecdotal evidence from users of Priceline and Hotwire' systems. Both adverse selection and hotel idiosyncratic demand shocks are hypotheses that can rationalize this pattern. The former is possible if star-rating captures hotels' quality imprecisely. That is, hotels with lower-than-average quality set lower wholesale prices and are therefore selected by the opaque platforms with a higher frequency than others. The quality differences not captured by the discrete star-rating are expected to be long lasting and therefore reflected in the dispersion of full-sample average prices. Alternatively, temporal idiosyncratic shocks might have a significant impact on pricing policies. If so, a hotel's position in the distribution of transparent rates is likely to change from date to date according to these shocks. When experiencing low demand, a hotel reduces its rates in *all* channels and is therefore expected to outbid other hotels in the opaque platform's reverse auction. Our findings are consistent with the latter hypothesis. The position in the contemporaneous distribution of transparent prices explains the probability of selling opaque while the position in the distribution of the full-sample average prices is not significant.

The paper is structured as follows. In Section 2 we discuss the economics of opaque selling and discuss predictions from the theory. The empirical specification, together with descriptions of the data and summary statistics are presented in Section 3. The econometric results are discussed and related to existing theories of opaque selling in Section 4. Section 5 concludes and highlights unexplored dimensions for future research.

2 Industry and theoretical background

Why do hotels engage in opaque selling? The short answer is that it allows them to segment demand and price discriminate business and leisure travelers similarly to how airlines price discriminate using Saturday stay-over requirements or early-booking discounts. However, there are new issues associated with opaque selling that make the price discrimination logic more intertwined. Before discussing the literature and economics of opaque selling, it helps to begin summarizing the main features of the travel industry.

First, though hotels book transparent rooms directly or through "passive" OTAs, they can only sell opaque through an active intermediary. The reason is that a third-party is required to pool hotels and create the opaque good hence buyer uncertainty.[13] Second, transparent and opaque channels coexist (sometimes offered by the same intermediary) and are easily accessed by customers. While the choice between buying directly from a hotel's website or from an OTA might be driven by buyers' search or switching costs, the choice between transparent and opaque bookings is primarily driven by heterogeneity in buyers' preferences. Third, the opaque wholesale market operates as a "reverse auction" and it is specific to each platform. Hotels submit their secret supply schedules (rates and number of rooms available) and the platform chooses the winner for each marginal transaction. Market clearing in the wholesale market is critical in determining the shape of competition in the opaque channel, its interaction with the transparent market, and the final effect on hotels' profits. Last, advance purchasing is a common practice in this industry and therefore dynamic pricing or revenue management considerations can impact both, transparent and opaque pricing strategies.

Aside from quality differences, hotels differ in many horizontal dimensions and so the demand faced by each hotel is not perfectly elastic. Selling through an opaque channel can help a hotel to attract consumers from the lower part of the demand curve without cannibalizing too much the sales to high-valuation consumers in the transparent market. Consumers can vary in their intrinsic willingness to pay as well as flexibility regarding the room characteristic: hotel brand, room usage date and room booking date. But they can also vary in their marginal utility of income. For example, other things equal, business travelers are expected to be less price sensitive than leisure travelers from the basic fact that their companies pay for their trips. In addition,

[13] In principle, a multiproduct firm (e.g., a hotel with different room-types) could sell opaque without the need of an intermediary. Maybe due to the lack of commitment by a seller of vertical differentiated products, we do not observed this in practice.

they present strong preferences regarding the hotel (closest to company headquarters) and room usage dates (weekdays). A conference or a meeting organized on a specific hotel and date make business travelers inflexible and willing to pay significantly more than a casual traveler that can reschedule her visit with little cost. In general, the literature refers to those price-insensitive customers as loyal customers. A non-loyal or shopper customer is price-sensitive and values most hotels similarly (which makes her even more price-sensitive).

Opaque products are inferior goods and can be thought of as a special case of damaged goods. Deneckere and McAfee (1996) and Shapiro and Varian (2000) showed that a monopolist can increase profits and welfare by selling a "damaged" version of the product to price-sensitive consumers. In a sense, the value destroyed by the producer of a damaged good might allow for the creation of even more value. This same logic underlies opaque selling. However, a key difference with the damaged good argument is that hotels selling opaque need to do so through the opaque platform and therefore compete aggressively for customers directly with other hotels.[14] Moreover, it is in the best interest of the platform to generate intense competition among hotels to capture a larger margin between the wholesale cost and customers' willingness to pay. Nevertheless, a successful platform is required to increase the utility of some type of customers *and* attract hotel participation. Low opaque prices impact hotels' profits directly and might also attract loyal customers to the opaque platform. In order to prevent cannibalization, price reductions in the transparent market might be needed, depressing profits even more. In that sense–and unlike in the damaged goods case–intense competition in the wholesale opaque market can make firms worse-off with opaque channels than without it. That is, while opaque selling destroys value to create more value, part of the value generated is captured by a new player. Much of the current debate in the industry is on the impact of opaque selling on hotels' profits. That is, entry by an opaque intermediary can increase hotels' profits but it is also possible that it creates a prisoner's dilemma making individual hotel participation profitable but lowering aggregate profits for hotels.

The theoretical literature has focused on the conditions required for opaque selling to increase industry profits. Fay (2008) and Shapiro and Shi (2008) show that price discrimination through opaque selling can be a successful strategy as long as consumers are sufficiently heterogeneous or products sufficiently differentiated. In their models, the market is segmented in equilibrium when the opaque prices attract

[14]By definition, hotels lose their market power in the opaque wholesale market since consumers self-selecting into the opaque channel are not willing to pay for product differences.

shoppers but are not low enough to attract the loyal customers.[15] In these cases, introducing opaque selling into fully-served markets increases industry profits at the expense of consumers' surplus. It is easy to see that opaque selling increases welfare if it also operates in the extensive margin selling to price-sensitive customers that would have otherwise not consumed. Tappata (2011) shows that this market expansion effect is larger in markets exposed to demand seasonality where the free-entry equilibrium leaves market gaps in the low-demand seasons.

It is important to note that the existing theories use very stylized models designed to explain the emergence opaque selling in a given industry.[16] We do not attempt to take these models literally to the data. Instead, we use them as a basic framework to think about opaque selling. There are two general predictions from the theory. First, significant consumer heterogeneity is required to justify the emergence of opaque selling. Second, conditionally on selling opaque, the difference between transparent and opaque prices increases with product differentiation.[17] A common feature from general price discrimination models is that the price in the no-discrimination scenario falls between the highest and lowest of the prices when the firm price discriminates. This might not be the case with opaque selling since prices for opaque and transparent prices can be lower than before the entry by the opaque intermediary (Tappata, 2011).[18] We can not test this prediction since we do not observe hotel prices before and after the emergence of opaque selling. Instead, we focus on the second prediction and explore how variables that vary across markets affect the magnitude of opaque discounts.

To fix ideas, consider a single market with $j \in J$ horizontally differentiated hotels. To isolate the effect of consumer heterogeneity on discounts, assume hotels have the same marginal cost mc and face symmetric demands. The equilibrium transparent and opaque rates (p^{τ}, p^{o}) are endogenously determined with the wholesale rate (w^{o}). This can be summarized in a single equation. Using the Lerner index and organiz-

[15] Formally, Fay (2008) assumes exogenous customer loyalty in a Hotelling duopoly while Shapiro and Shi (2008) model two groups of buyers, one with low and one with high transportation costs, in a circular city.

[16] For tractability purposes, they only allow for few dimensions of heterogeneity among consumers and firms. Moreover, firms are not allowed to price discriminate consumers in the absence of opaque selling. Similarly, competition between opaque platforms is not modeled.

[17] In the duopoly model of Fay (2008) for example, a symmetric equilibrium predicts a larger gap between transparent and opaque prices when consumers face larger transportation costs and the proportion of loyal customers is larger. In Tappata (2011), the gap increases with transportation cost and the distance separating firms.

[18] More formally, different modeling choices (e.g. exogenous vs endogenous loyalty) can lead to transparent and opaque prices being strategic substitute or complements.

ing terms, the opaque discount associated with hotel's h transparent price can be expressed as

$$Disc_h = 1 - \frac{p^o}{p_h^\tau} = 1 - \frac{w^o}{mc}\left[\frac{\epsilon^o/(\epsilon^o - 1)}{\epsilon_h^\tau/(\epsilon_h^\tau - 1)}\right] \tag{1}$$

where ϵ^o and ϵ_h^τ represent the absolute value of the demand elasticity for opaque and hotel h's bookings respectively.[19] Note that, since $w^o \geq mc$, a necessary condition for positive discounts is $\epsilon^o > \epsilon_h^\tau$. We now turn to the determinants of these elasticities.

Assume consumers have unit demands and their preferences are characterized by the distribution of reservation values v_j over the J transparent alternatives. Important to the analysis of opaque selling is the entire distribution of valuations. To simplify it even further, assume that all consumers have the same average valuation $avg(v_j) = \bar{v}$. While the maximum valuation is relevant to choose among the transparent hotels, the difference between this maximum and a weighted average of the J values determines the relative preference for opaque bookings. Consumers with dispersed preferences are expected to face significant disutility from buying opaque (i.e., $max(v_j) - \bar{v}$ large). On the other hand, consumers with fairly concentrated reservation values are likely buyers of opaque products.[20] Their expected utility from buying a lottery is not very different from the utility obtained when booking their preferred transparent hotel.[21]

We illustrate the relationship between the demand for transparent and opaque goods in Figure 1. A hotel's market power is captured by the firm-demand elasticity ϵ_j^τ which is determined by the number of hotels in the market, the extent of product differentiation, and consumers' price sensitivity. This is represented by the solid black curve on Figure 1. Given a pair of transparent and opaque prices p^τ and $p^o < \bar{v}$, the demand for opaque bookings faced by the platform is determined as follows. First, hotel k's residual demand includes all consumers for which $max(v_j) = v_k < p^\tau + \bar{v} - p^o$. The residual demand is always more price-elastic than the original demand.[22] Second, the residual demand from each hotel "shifts down" to reflect the fact that opaque goods are inferior goods relative to transparent goods. That is, the willingness to pay for an opaque good must be discounted since consumers' willingness to pay for an opaque booking is associated with $\bar{v}$ instead of $max(v_j)$. The shift in the demand is not expected to be symmetric as the disutility from opaque bookings is negatively

[19] In our example, hotel prices and elasticities are symmetric in equilibrium. We keep subscript h to differentiate between the firm and market demand for transparent bookings.

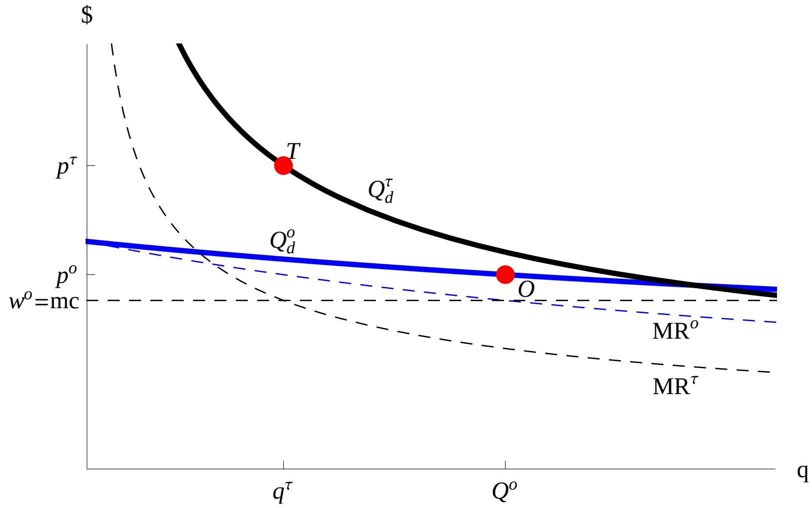
[20] In the one-dimension address models, this is represented by the interaction between consumer's distance to the products' locations and transportation cost parameter.

[21] It is easy to see the effect of adding risk aversion on the relative demand for opaque bookings.

[22] If $q = f(p)$ such that there is p^* that maximizes profits, $\epsilon = f'(p)p/f(p)$. The residual demand $q^R = f(p) - q^*$ has elasticity $\epsilon^R = f'(p)p/[f(p) - q^*] > \epsilon$.

correlated with consumers' willingness to pay for the transparent booking. Last, the J–modified–residual demands are aggregated and determine the demand for opaque bookings (blue curve in Figure 1).[23]

Figure 1: Equilibrium in the Transparent and Opaque Markets



Note: Firm-level demand and marginal revenue for transparent bookings in black (Q^τ and MR^τ). Demand for opaque bookings and marginal revenue in blue (Q^o and MR^o). Wholesale price for opaque room assumed equal to marginal cost.

As equation 1 shows, the magnitude of the opaque discount is related to supply and demand factors. For example, as the theory suggests, more product differentiation leads to higher discounts. An increase in product differentiation is equivalent to an increase in the dispersion of consumers' valuations over the J available alternatives. That is, $maxv_j$ increases for each consumer but $\bar{v}$ remains constant. Thus, the hotel-level demands become more elastic (higher ϵ^τ) but the elasticity for opaque bookings is not affected. We can also explore the different channels through which competition affects predicted discounts. First, we expect more firms to intensify competition and lower transparent prices. The impact of lower transparent prices on ϵ^τ is translated to the residual demand (ϵ^o) and therefore discounts might not change. Second, a change in the number of firms affects competition in the wholesale market. We expect competition in the wholesale market to increase $Disc_h$ as w^o approaches mc from above. Third, more firms can affect consumers' valuations similarly to product differentiation (i.e., increase $maxv_j$ for all consumers holding $\bar{v}$ constant). Other comparative statics can be analyzed with equation (1) and we postpone their discussion until Section 4.

[23]Note that the last two steps do not affect the price-elasticity of demand.

The forces underlying opaque selling discussed above are present in static models and we have so far ignored dynamic elements associated with demand uncertainty and capacity constrained firms, two important dimensions in the travel industry. As mentioned above, leisure travelers booking early in advance and business travelers on dates closer to the consumption date. Exploiting the correlation between room-booking date and willingness to pay has been the main reason for the use of revenue management programs in the industry. However, the incentive to use dynamic pricing might be attenuated for a hotel once it can use the opaque channel to cater price-sensitive consumers (leisure travelers). For example, Jerath et al. (2010) present a two period model where firms can choose to use the opaque market only in the last-minute to sell excessive inventory. A hotel would prefer to use the competitive opaque market in the last-minute to discounts in the transparent market if product differentiation is large enough to keep loyal buyers away from leaking to the opaque market. Otherwise, hotels avoid the opaque market altogether and sell excess inventory (if any) at a discount in the transparent market. As we explain in the next section, the structure of our data allows us to test whether opaque selling is a last-minute practice in this industry.

3 Data and Empirical Specification

3.1 Matching opaque and transparent data

Our data contains opaque and transparent hotel room rates combined with hotel and market characteristics. In order to describe these data, it is helpful to define first the unit of analysis more precisely. A "booked room" j is defined by the set of attributes $\{h, r, b, t\}$ where h is the hotel identity, r the room-type (non-refundable, standard, with view, bedding, etc), b the booking date and t the check-in date. In other words, we define a hotel room j as the product observed by the buyer at the time of consumption (check-in date) instead of purchase (booking date). Note that, since opaque and transparent products only differ at the time of purchase, consumers' information about h varies depending on whether the room was booked through the opaque or the transparent channels. The opaque and transparent hotel rates were obtained from different sources. We refer to them as the opaque and transparent data. A major challenge involves the matching of each price paid in the opaque platforms (p_j^o) to the relevant transparent posted price (p_j^τ). We explain the main features of this process in this section and leave the details to Appendix B.

The opaque data includes room bookings made on Priceline's NYOP system and

Hotwire's SHR listings. The source is the website Betterbidding.com, a forum created to benefit users of these two popular platforms. The different sites in the forum are designed so that users discuss strategies, share experiences and exchange detailed information on their opaque bookings. Forum participants routinely post the identity of the hotel, rate paid and dates when booking through Hotwire or from a winning bid on Priceline. We have compiled and parsed these posts for the most popular destinations in North America. We emphasize that the nature of opaque bookings makes it impossible to obtain transaction-level information from sources other than the opaque platforms. Though price-protection is a feature that attracts hotels to the opaque platform, the secrecy goes beyond potential buyers and even hotels are not aware of the rates consumers pay the opaque platforms. Self-reported data has become available recently and this is the first study using these data to analyze opaque pricing.

It must be noted that it is not clear whether forum participants represent the average user of opaque platforms. On the one hand, one expects forum participant to be frequent travelers willing to invest time and effort to obtain better-than-average deals. On the other hand, inexperienced users are the ones most likely to seek information and report back in these forums. This is a common issue with user-reported data in the IO literature.[24,25] In addition, there is the possibility that hotels or the opaque platforms create fake posts in the forum to bias expectations over opaque booking outcomes. Mayzlin et al. (2013) show that there is evidence of manipulation of product reviews when anyone, instead of just consumers, can post them. We note first that the benefits from faking booking rates for these firms are not as clear as in the case of product reviews.[26] Moreover, even though the cost of generating a fake post is similar to the cost of a fake product reviews, the benefits are far lower since forum posts get easily outdated. User accounts are required to post information on opaque bookings. A look at the distribution of posts by user reassures us that information manipulation is unlikely. We find that users with four or less posts represent 95% of the opaque bookings in our sample.[27]

[24] Examples of work that use self-reported data include Lewis (2008) and Dai et al. (2012). The former uses gasoline prices reported by drivers to GasBuddy.com and the latter uses retail store's ratings from users of Yelp.com.

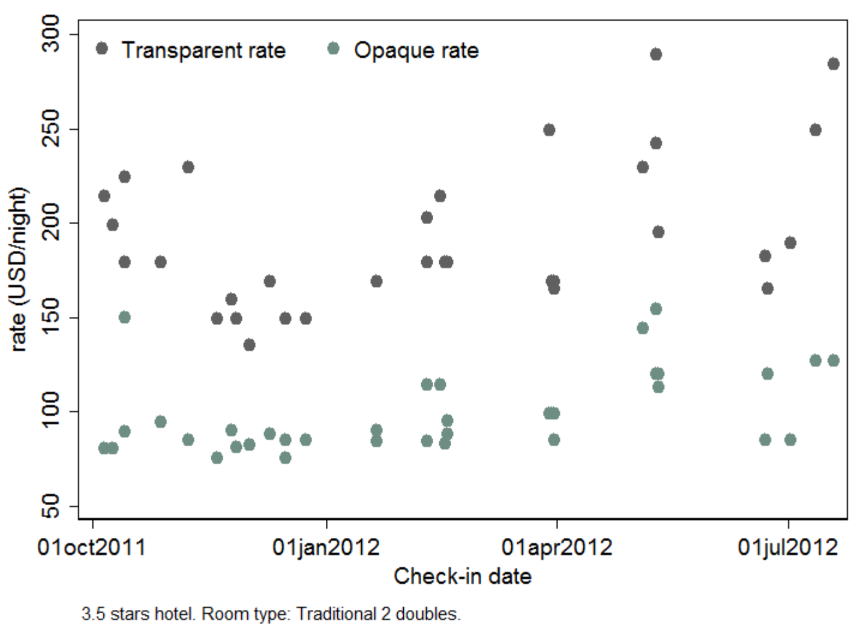
[25] Sample bias, if any, would primarily affect Priceline's auction-based bookings since buyer's bidding abilities do not influence the posted offers on Hotwire.

[26] For example, Priceline and Hotwire both announce on their website the expected savings for consumers. These savings are consistent with the opaque discounts in our data.

[27] The user with most active participation contributed with posts for 14 opaque bookings on nine different hotels in NYC.

We paired each booked room j in the opaque data to a room rate posted in the transparent channel. To do so, we first collected one-night transparent room rates from Hotels.com for the largest cities in Canada and the US from October 1, 2011 to June 25, 2012.[28] For each booking date b, we recorded the website's posted rates offered by all hotels in the city allowing for check-in dates $t = \{b, b+1, ..., b+90\}$. Note that this data with transparent room rates is very large and includes rates for all room types and booking/check-in date combinations quoted by more than 5,000 hotels (i.e., about 8.1 million transparent rates per day). Such detailed data allows us to do a proper match between opaque and transparent rates controlling for all the attributes that define a booked room j. The rooms booked through Priceline or Hotwire are non-refundable standard rooms. Thus, each opaque booking was matched to the price quoted by the same hotel for its cheapest room quoted on the same check-in date and, when possible, the same booking date. As explained in Appendix B, if the latter condition was not met, we selected the transparent rate with closest booking date that satisfied the other restrictions.

Figure 2: Matched bookings. Westin Bonaventure Hotel, LA



Note: Each opaque booking in the Westin Bonaventure hotel is characterized by the triple (booking-date, check-in date and room-type). The figure displays the opaque rate paid and the transparent rate a customer would have paid if booked through the transparent channel (hotels.com) on the same booking-date.

[28]We have also included rates from a small sample of New York City hotels from March to October 2011.

To illustrate the rate-pairing procedure, Figure 2 displays the check-in date and room rates (transparent and opaque) for the 37 matches made for the Westin Bonaventure Hotel in Downtown Los Angeles. For example, the first pair of observations from the left in the figure corresponds to a Priceline booking made for $80/night on Oct 3, 2011 with check-in date Oct 6. From the transparent data, we find that the rate for "same" room was quoted at $214/night (i.e., 62% discount). The figure shows that transparent and opaque rates set by the same hotel vary significantly as well as the implied opaque discounts. Not shown in the figure are other sources of variation like the opaque platform used, booking date, day of the week, and duration of stay. To highlight the dimension of the transparent data required for the matchings in the figure, only 37 of the 37,564 transparent rates collected for the Westin Bonaventure Hotel in Los Angeles were used. We take advantage of the full transparent data to create variables that capture market and competitor's characteristics as well as to investigate the position of hotels selling opaque on the distribution of transparent rates. We discuss these variables and present summary statistics after describing the econometric specifications.

3.2 Empirical specification

The main goal of this paper is to rigorously document opaque pricing and provide answers to the following questions: What is the discount required by a consumer that books opaquely instead of using the transparent channel? Do consumers view posted-price and auction-based opaque selling systems as equivalent? What is the effect of the opacity level on the willingness to pay for opaque bookings? Are opaque bookings a last-minute practice in the industry? Do hotels price discriminate intertemporarily within channel? Are opaque discounts different across quality segments? To investigate these questions we first estimate a general discount equation. We further explore the determinants of opaque and transparent rates by analyzing pricing equations for each channel separately. The baseline specifications are as follows:

$$Disc_j = \delta_0 + \delta_1 Platform + \delta_2 X_{hr} + \delta_3 X_{bt} + u_j \quad (2)$$

$$\ln p_j^\tau = \beta_\tau + \gamma_\tau X_{hr} + \alpha_\tau X_{bt} + v_j^\tau \quad (3)$$

$$\ln p_j^o = \beta_o + \lambda Platform + \gamma_o X_{hr} + \alpha_o X_{bt} + v_j^o \quad (4)$$

with $Disc_j = 1 - p_j^o/p_j^\tau$. The vector X_{hr} includes covariates associated to hotel room and market fixed characteristics. Hotel-room attributes are hotel quality (star rating), a dummy variables identifying hotels that belong to large chains and refundable rooms sold in the transparent channel (only in equations 2 and 3).

The static market characteristics are captured by city fixed-effects and local market metrics (e.g., number of competitors, opaque area size, dispersion of hotels' locations, airport dummy). The number of hotels in a market influences pricing in all channels and is potentially correlated with unobservables. We instrument the number of firms using the office rent cost per area.[29] This instrument proxies the fixed cost faced by hotels which impacts firms' entry/exit decisions and therefore is expected to be correlated with the number of firms in the market. At the same time, fixed costs do not enter in the hotels' pricing equation. The dummy variable *Platform* (=1 if Hotwire is used) captures the premium consumers place on posted-price instead of auction-based selling systems. To summarize, the estimated coefficients δ_1 and δ_2 in equation (2) inform us of the extent to which hotels use selling channels to screen consumers based on preferences and transaction costs in a static sense.

Our data allows us to detect price and discount variation between and within platforms. In principle, Hotels can segment their demand by setting different prices between selling channels as well as within a selling channel. In the latter case, pricing can differ based on the check-in date or advance booking (days between booking and check-in dates) variables. This has been a common practice in the airline, hotel and rental car industries to segment leisure travelers from business travelers since the former are more likely to book earlier and on weekends. The vector X_{bt} include dynamic variables that capture changes in demand composition (i.e., elasticity of the demand curve faced by each hotel in each channel). Statistic significance of δ_3 would indicate that hotels use these within-platform segmentation practices.

We use indicators for weekend/weekday check-in dates, advance bookings and a proxy for temporal demand shocks. Time-related demand shifts affect the hotel's likelihood of binding capacity constraints. A hotel's marginal cost at booking time b is composed by the cost of servicing a room and the opportunity cost of not selling it at a higher price on a date closer to the check-in date t. While the former can be assumed constant, the latter depends on the probability, at time b, of reaching full capacity before date t. We do not observe hotels' marginal costs. Instead, we proxy demand fluctuations using Google Trend's weekly measures of search popularity (SPI) for each destination city. Unlike city fixed-effects, the SPI is a relative measure of

[29] Asking rent values were obtained from Jones Lang LaSalle's (www.joneslanglasalle.com). Details on the construction of our instrumental variable and summary statistics are provided in the Appendix B.3.

search popularity that captures variation of popularity across cities and over time. We describe this variable in more detail in the Appendix B.4.

3.3 Descriptive statistics

Table 1 presents the summary statistics of the variables used in the estimation of equations 2–4.[30] On average, an opaque booking allows the buyer to obtain a 44% discount with respect to the transparent rate. The average transparent and opaque rates are \$187 and \$100 dollars per night respectively. Both, opaque and transparent, markets present significant rate dispersion. This variation is mainly influenced by hotel quality rating and city effects (Figure 4 in Appendix A) although, as shown in Figure 2, the rate dispersion for a given hotel can still be very large.[31]

Table 1: Summary Statistics

Variable	Mean	SD	Med	Min	Max
Discount (%)	44.0	16.4	44.7	-37.9	90.3
Transparent Rate (USD)	187	87	168	29	803
Opaque Rate (USD)	100	49	90	13	380
Non–refund = 1	0.30	0.46	0	0	1
Platform (Hotwire = 1)	0.31	0.46	0	0	1
Chain = 1	0.68	0.47	1	0	1
Stars	3.73	0.65	4	2	5
Weekend	0.52	0.50	1	0	1
Adv Booking (weeks)	4.29	4.62	3	0	28
SPI	40.98	24.30	34	3	100
Airport = 1	0.11	0.32	0	0	1
Area size (sqmi)	7.8	13.1	2.2	0.1	107.6
Dispersion = Var(dist)	0.3	1.0	0.1	0.0	19.1
Comp 1/2mi	15.0	16.3	8	0	73
Hotels of = star in area	7.9	5.2	6	1	35

Bookings in our sample are twice more likely to be done on the auction-based (Priceline) than in the posted-price (Hotwire) channel. As shown by Figure 3(a), some of the opaque bookings have negative discounts (34 observations). Although we do not expect opaque rates to be higher than transparent rates, we cannot discard this event and therefore decided to keep the observations in the data.[32] Hotel quality

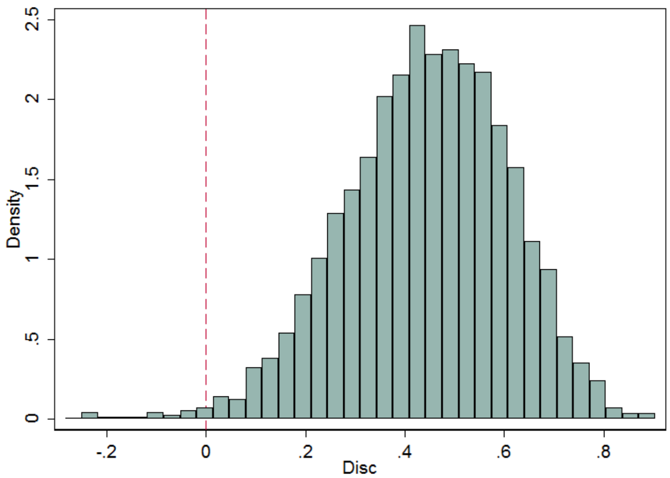
[30]See Table 4 in Appendix B for the definition of each variable.

[31]Hotel stars and city fixed effects explain 13.6% of the variance in discounts and about 45% of the transparent and opaque rates variance.

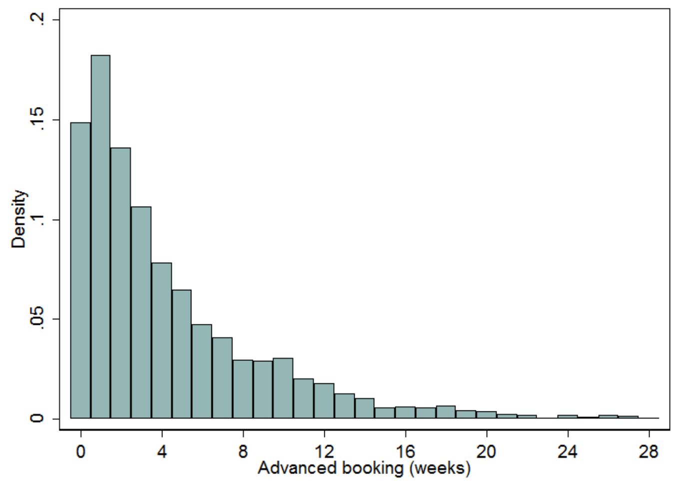
[32]Negative discounts are expected to be more likely in bookings through Priceline since the possibility of consumer "mistakes" are larger. However, only 12 of the 34 bookings with negative discounts were done through Priceline's channel.

is measured by the seven hotel star-rating levels: 2, 2.5, 3, 3.5, 4, 4.5 and 5 stars. The average hotel quality rating is 3.7 stars and half of the transactions occurred in 4-star and higher hotels. Although the mean quality is similar across platforms, bookings on Priceline are more likely to be of higher quality than those on Hotwire. Moreover, opaque bookings in general are done in hotels of higher quality than that of a random hotel in the market (Figure 3(a) in Appendix A).

Figure 3: Discounts and early bookings distributions



(a) Opaque Discounts: $(1 - p^o/p^\tau)$



(b) Advanced Bookings

We observe significant heterogeneity in the booking dates. The average booking is made about 30 days in advance. The median booking is done 3 weeks in advance and 3/4 of the bookings are done within 6 weeks of the check-in date. The distribution of advance bookings, shown in Figure 3(b), reveals that the opaque channels are open to consumers well in advance to the check-in date. This evidence is in conflict with the idea that the opaque channel is active only at the last minute so hotels can sell their distressed inventory. We test whether advance bookings affect the size of the discounts when estimating equation (2) in the next section. Motivated by Figure 5(b) in Appendix A, we allow for non-linear effects of Advance-Booking on Discounts. The dummy variable *Weekend* (stay over on Friday or Saturday night) includes the night before a holiday in the US or Canada to capture demand from non-business travelers. About half of the opaque transactions occur on a weekend. Figure 3(b) in Appendix A complements this statistic with the distribution of bookings over the different days of the week.

The Search Popularity Index (SPI) takes values between 0 and 100 and varies across cities and time. Figure 5(d) in Appendix A shows the SPI variability in four different cities. The SPI level for a given city fluctuates significantly showing in some cases evidence of seasonality.[33] We use the dummy varables *Chain* and *Non-refund* as controls. The former identifies hotels that belong to a large and recognizable chain. Presumably, these hotels have more advance reservation system in place and can take advantage of the opaque channel by dynamically updating inventory and adjusting rates at a higher frequency than stand-alone hotels. Most of the opaque bookings (68%) are done in hotels that belong to chains. However, this is not very different from the proportions of chain-hotels in the population (69%).[34] By definition, opaque bookings are non-refundable and therefore should be compared to a non-refundable transparent rate to avoid overestimation of the discounts. The transparent rates that matched the remaining attributes of our opaque booking are more likely to be refundable rates and only in 31% of the cases the transparent rate is non-refundable.

The variables in the bottom of Table 1 vary across markets and are associated with product differentiation, competition and the opacity level of opaque bookings. We calculated the walking distance between all hotels in a given city using Google maps application and used it to determine, for each hotel, the number of hotels within a distance threshold (*Comp*). We repeated this procedure for hotels of equal (*Comp_same*) and similar (*Comp_sim*) star rating (plus/minus 0.5 stars). On average, a hotel has 14 competitors within half a mile of walking distance. Four of those competitors have the same star-rating (not reported in table). The opacity level of a given booking is captured by the opaque area size (*Area size* in squared miles) and the variance of the distance between each hotel and the weighted-centroid for the opaque area (*Dispersion*). A larger variance relates to a clumped pattern of hotels. Last, 11 percent of our observations fall in airport areas where we expect different demand and therefore price dynamics than in the rest of the city areas.

Table 2 provides additional information regarding the dependent variables in equations 2–4. Opaque discounts are about 9 percentage points larger when opaque bookings are done through auction-based (Priceline) instead of posted-price system. The variance in discounts is similar across opaque platforms and, as Figure 3(c) in Appendix A shows, this seems true for higher moments of the distribution of discounts.

[33] The U.S. Travel Association and American Express in their "Destination Travel Insights" provide a ranking with the top 20 cities based on the number of leisure and business travelers in United States. The positions in 2013Q1 for Chicago, Las Vegas and Miami are, respectively, 4, 15, and 8 in the "business destination" ranking and 3, 5, and 8 in "leisure destination" ranking (http://www.ustravel.org/research/destination-insights).

[34] These two numbers are not strictly comparable. It is more common that a hotel belongs to a chain if it has a low star-rating. And opaque bookings are generally done in high quality hotels (thus, less likely to belong to chains).

Table 2: Summary Statistics–Dependent Variables

			Room rates				Discounts %	
			Transparent		Opaque			
		N	Mean	SD	Mean	SD	Mean	SD
Platform	Priceline	2,650	190	87.85	97	47.05	46.71	15.58
	Hotwire	1,167	179	85.4	107	52.26	37.99	16.56
Stars	2	90	95	36.5	66	29.38	29.19	17.74
	2.5	175	109	33.83	66	25.03	38.85	17.66
	3	537	150	78.23	80	48.13	45.89	14.46
	3.5	918	166	65.11	84.0	36.15	46.6	17.17
	4	1,636	215	91.61	113	49.63	45.21	15.88
	4.5	125	266	104.18	155	66.61	39.88	16.41
	5	336	200	64.55	122	32.92	36.7	13.32
Chain	0	1,239	194	87.59	109	50.6	41.48	16.67
	1	2,578	183	86.91	96	47.55	45.28	16.1

Note however that the difference in mean discount might be jointly explained by the selling system and the hotel quality segment. As we mentioned before, Hotwire bookings are done in lower quality hotels than those on Priceline and the table shows that discounts seem larger in the higher star-rating segment. Interestingly, the distributions of transparent and opaque rates for each star level differ beyond the first moment.[35] Figure 6(a) in the Appendix shows that transparent rates are more spread out than opaque rates. But this is less so for lower quality hotels (2 and 2.5 stars on Figure 6(b)). We get back to this point in the next section.

4 Results

4.1 Discount equation

We start reporting results from the estimation of equation (2). Table 3 presents four specifications where the dependent variable ($Disc_j * 100$) measures the savings by booking in the opaque relative to the transparent channel. All specifications include city-level fixed effects and use robust standard errors clustered at the hotel level. Our preferred specification is given in column (4) where we instrument the competition variable *Comp 0.5mi* using the office rental cost per square feet ($\$psf$).[36] Given that

[35]The lower hotel rates in 5-star relative to 4.5-star hotels is driven by the fact that all but one of those hotels are located in Las Vegas, a cheaper destination than the average city in our sample.

[36]The number of observations in column (4) is reduced because rent data for Las Vegas and Niagara Falls are not available.

the estimated coefficients do not vary substantially across specification we mainly discuss the results reported in column (4).[37]

The main explanatory variables affecting opaque discounts are platform used and hotel's quality. The coefficient for *Platform* shows that the 9 percentage points difference in unconditional discounts between Priceline and Hotwire (Table 2) is robust to the inclusion of all our covariates. After accounting for non-refundability, the expected discounts are 49.2% for opaque bookings made on Priceline and 39.5% for opaque bookings made on Hotwire. Given the supply-side similarities of these two platforms, we attribute the sign and magnitude of the *Platform* coefficient to the frictions involved in the NYOP bidding system. In particular, the transaction costs imposed to buyers due to the multiple bidding restrictions. Note however that this represents an upper bound of the effect of auction-based, instead of posted-price selling systems. The differences in discounts could also be attributed to the sometimes lower uncertainty faced by Hotwire's users. A hotel room is a bundle of attributes each valued differently by consumers. Some have strong preferences over specific hotel location within the opaque area, others on the amenities available, and other consumers might just care about the hotel identity (e.g., to obtain loyalty rewards). Conditional on buying opaque, and Hotwire releasing more information about the opaque hotel than Priceline (e.g., swimming pool availability), the expected utility for these consumers would be higher if buying through Hotwire. The reason is that buyers can update their—uniform—prior probabilities attached to each hotel in a given opaque area.[38] We argue that the information component of the discount spread across platforms is unlikely to be large. First, as can be observed from Figures 1 and 2 in Appendix A, only in few instances the information regarding an opaque hotel's amenities are different from those expected from a hotel of a given star-rating. Second, as we show below, the opacity level has little effect on the size of the observed discounts.

Better deals are obtained when booking higher quality hotels. Discounts increase on average by 6.62 percentage points for each full unit increase in *Stars*.[39] The boxplot in Figure 4 shows the monotonic relation between predicted discounts, hotel star-rating and selling platform. Hotel rates in each channel are bounded by consumers' willingness to pay and the marginal cost of providing a room with the exact level

[37]We fail to reject the null hypothesis of exogenous *Comp 0.5mi*.

[38]Note that the logic is conditional on buying opaque. Buyers with strong preferences over a hotel's amenity would most likely use the transparent channel.

[39]This result is similar across platforms and robust to other non-linear specifications (e.g., star level dummies).

Table 3: Discount Regressions
Dependent variable: $Disc_j * 100$

	(1)	(2)	(3)	(4)
Platform (Hotwire=1)	-8.619***	-8.679***	-8.645***	-9.328***
	(0.694)	(0.688)	(0.678)	(0.726)
Non–refund	-2.814***	-1.688	-1.714	-1.340
	(0.839)	(0.990)	(0.948)	(0.934)
Chain	0.782	0.888	0.614	0.865
	(1.369)	(1.390)	(1.365)	(1.192)
Stars	3.107***	3.598***	3.588***	5.285***
	(0.857)	(1.022)	(1.067)	(1.218)
Airport = 1	2.595	2.529	1.564	1.908
	(1.451)	(1.465)	(1.421)	(1.409)
Weekend		0.151	0.303	2.413
		(3.308)	(3.262)	(3.994)
Wknd*Stars		-0.695	-0.746	-1.498
		(0.854)	(0.844)	(1.073)
Adv Booking (wks)		-0.426**	-0.387*	-0.282
		(0.159)	(0.158)	(0.167)
AdvBook^2		0.025***	0.023***	0.021**
		(0.007)	(0.007)	(0.008)
NonRef*AdvBook		-0.213	-0.217	-0.285*
		(0.131)	(0.128)	(0.129)
SPI		0.077	0.076	0.013
		(0.042)	(0.042)	(0.047)
Area size (sqmi)			0.081*	0.081*
			(0.037)	(0.038)
Dispersion=Var(distance)			-1.473***	-1.119**
			(0.417)	(0.355)
Comp 0.5mi			-0.075*	-0.130
			(0.036)	(0.090)
Constant	43.480***	41.490***	42.616***	38.159***
	(3.588)	(4.239)	(4.498)	(4.862)
City fixed effects	Yes	Yes	Yes	Yes
R-squared	0.194	0.205	0.213	0.222
N	3817	3817	3817	3180
Underidentification:				
Kleibergen-Paap rk LM statistic				28.426
Chi-sq (p-val)				0.000
Weak identification:				
Kleibergen-Paap rk Wald F statistic				63.592

Robust standard errors clustered at the hotel level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 2-step GMM with *Comp 5mi* instrumented in Column (4).

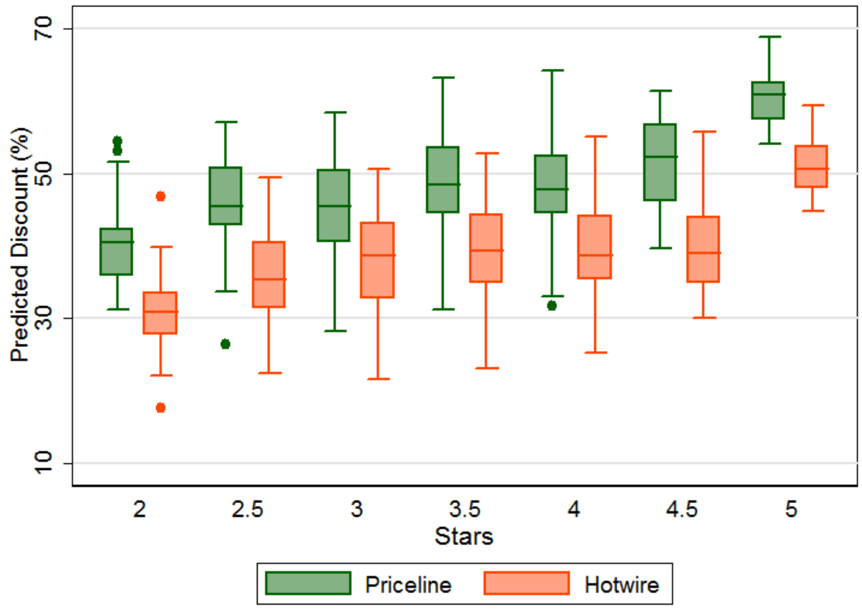
being determined by competition in the marketplace. Naturally, all else equal, these bounds increase with a hotel's quality explaining why transparent and opaque rates increase with star ratings. We find that quality affects transparent rates more than opaque rates and this is consistent with the combination of some of the following elements: (i) strong competition in the wholesale opaque markets, (ii) demand for transparent products in the low quality segment is more elastic than in the high quality, (iii) the demand for opaque products in the high quality segment is more elastic than in the low quality segment. The first is intuitive since the reverse auction implemented by the opaque platform removes product differentiation and therefore, delivers a low wholesale cost to the platform.[40] Note however that condition (i) alone is not sufficient to explain the larger discounts for higher quality hotels observed in the data. Aside from the wholesale cost of the opaque room, the intermediary must face a more elastic demand in the opaque market for hotels with higher star-rating. This could be due to the fact that consumers in the high quality segment have more dispersed preferences than those in the low quality segment. This leads to a more inelastic demand in the tranparent segment and higher elasticity in the opaque market since consumers' valuations for opaque goods become less dispersed. Moreover, as the constant gap across platforms in the figure suggests, the effect described above does not seem to be asymmetric among consumers with different transaction costs.[41] On a side note, it is interesting that Priceline provides their customers the city-area and star-level where best deals can be obtained. Consistent with our findings, the "best deals" recommend ed for the bookings in our database are 66% of the time for 4-star hotels and only 0.02% of the time for a 2-star hotel.

Notably, the remaining coefficients in Table 3 are either insignificant or have a very small economic impact on opaque discounts. First, discounts by hotels associated to large chains are not different from those at other hotels. Although the definition used for *Chain* is somewhat subjective, the results do not change when alternative definitions are used (e.g., the ten largest chains in the industry only). Second, it appears that the traditional price discrimination practices in the travel industry, if any, are not different in the transparent and opaque markets. Discounts on check-in dates associated with demand driven by leisure travelers are not different than discounts on other dates. The estimated coefficient for the *Weekend* is positive yet not statistically significantly different from zero. The insignificant coefficient for the interaction term between the variables *Weekend* and *Stars* grants that we are not

[40] In a truly Bertrand Paradox environment the wholesale cost equals the hotel marginal cost.

[41] We estimated equation 2 including the interaction term between *Platform* and *Stars* and found the coefficient insignificant (not reported and available upon request).

Figure 4: Predicted Opaque and Semi-Opaque Discounts



masking a situation where high and low star-rated hotels have inverse pricing policies regarding weekend and weekdays.

More importantly, discounts are weakly affected by advanced bookings. The point estimates suggest a non-linear relationship where, relative to last-minute booking, the opaque discounts are larger if booked more than 13.5 weeks in advance. The worst time to book opaque being around seven weeks in advance (-0.78 percentage points). However, only the quadratic term is significant at the 10 percent level suggesting that the median booking (three weeks in advance) obtains a discount that is only 0.15 percentage points higher than a last-minute booking.[42] This result, combined with the null effect of demand shocks (SPI) on opaque discounts and the fact that the average opaque bookings occurs 4 weeks in advance of the check-in date (Figure 3 and Table 2), supports the static price discrimination theories described in Section 2 and rejects the notion that hotels use opaque channels as a last minute resource to dispose of their unsold inventory.

Surprisingly, the size of the opaque area on discounts is not statistically significant in column (4). As expected, the coefficient is positive meaning that consumers require larger discounts for bookings that have higher opacity level. But this effect is small:

[42]The quadratic term used in the specification captures most of the non-linear effects of *Advanced Booking* on Discounts. Figure 7 in Appendix A shows that the residuals from the regression in column (4) are indistinguishable from each other.

a one standard deviation increase in *Area size* leads to only one tenth of a percentage point increase in opaque discounts. We find discounts to be about 0.8 percentage points lower in areas where hotels are one standard deviation more "dispersed". Note that, our dispersion variable measures the variance in hotels' distances to the area centroid. That is, more dispersion means that the spatial distribution of hotels is asymmetric allowing for the possibility of local clusters. Last, discounts are not influenced by the number of firms in the market nor whether the hotel is located in an airport. We note that these results do not mean that the covariates have insignificant economic impact in the equilibrium of the transparent and opaque markets. The observed discounts might mask symmetric impact of these variables in each market. We return to this when present the pricing equation results.

The main takeaway from Table 3 is that the discounts offered by hotels fit the predictions from the simple (static) mechanisms of demand segmentation when consumers have heterogeneous preferences among product attributes. As expected, customers booking in opaque markets obtain substantial discounts in exchange for not observing information about their service providers. The discounts in the posted-price platform are lower than in the auction-based platform and reflect the role of transaction costs in segmenting further opaque users. Regardless of platform, opaque discounts increase monotonically with hotel star-rating. Last, the evidence supports the idea that opaque bookings are a tool for price discrimination that is used regularly by hotels and not as a last-minute resource. We now turn to the analysis of the pricing equations to get a better understanding of the mechanisms underlying the discounts results.

4.2 Price equations

We now present the results from estimating the pricing equations (3) and (4). Tables 4 and 5 show, for transparent and opaque rates respectively, similar specifications to the ones used when estimated the discount equation. As before, we focus on results reported on column (4) and analyze the estimated coefficients for opaque and transparent rates jointly.

As expected, the major impact on hotel transparent rates—together with destination city—is given by hotels' star rating. Transparent room rates increase by about 44% ($exp(0.369) - 1$) with each additional star in a hotel's quality rating. To put this magnitude in perspective, the largest city fixed effect (Washington, DC) shifts transparent rates by 39% relative to the baseline—and cheapest—city (Atlanta). Con-

Table 4: Price Regressions. Transparent Bookings
Dependent variable: $\ln p_j^{\tau}$

	(1)	(2)	(3)	(4)
Non–refund	-0.094***	-0.102***	-0.101***	-0.093***
	(0.019)	(0.022)	(0.022)	(0.023)
Chain	0.023	0.031	0.033	0.032
	(0.029)	(0.028)	(0.029)	(0.028)
Stars	0.358***	0.348***	0.342***	0.350***
	(0.022)	(0.023)	(0.024)	(0.024)
Airport = 1	-0.176***	-0.176***	-0.161***	-0.164***
	(0.033)	(0.033)	(0.032)	(0.031)
Weekend		-0.185*	-0.179*	0.004
		(0.085)	(0.085)	(0.079)
Wknd*Stars		0.039	0.037	-0.026
		(0.023)	(0.024)	(0.022)
Adv Booking (wks)		0.007	0.006	0.009*
		(0.004)	(0.004)	(0.004)
AdvBook^2		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
NonRef*AdvBook		0.001	0.000	-0.002
		(0.003)	(0.003)	(0.003)
SPI		0.007***	0.007***	0.008***
		(0.001)	(0.001)	(0.001)
Comp 0.5mi			0.002	0.003
			(0.001)	(0.002)
Constant	3.614***	3.510***	3.512***	3.456***
	(0.086)	(0.095)	(0.094)	(0.092)
City fixed effects	Yes	Yes	Yes	Yes
R-squared	0.506	0.522	0.525	0.554
N	3817	3817	3817	3180
Underidentification:				
Kleibergen-Paap rk LM statistic				34.659
Chi-sq (p-val)				0.000
Weak identification:				
Kleibergen-Paap rk Wald F statistic				77.546

Robust standard errors clustered at the hotel level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 2-step GMM with *Comp 5mi* instrumented in Column (4).

sistent with the monotonic relationship between stars and discounts discussed above, opaque rates increase by only 26.5% with hotel's quality.[43] Similarly, the *Platform* coefficient on Table 5 shows that opaque rooms are 16% more expensive when booked using Hotwire's posted-price system rather than bidding on Priceline's NYOP system.

The price premium for a refundable room is about 10% (Table 4). Refundable rooms offer buyers in the transparent market the opportunity to cancel a booking at no cost before the check-in date. In principle, the premium for refundable rooms in competitive markets reflects this option-value to consumers and therefore converges to zero as the booking date approaches the check-in date (i.e., as consumers' uncertainty is resolved). Interestingly, we do not observe such convergence: the coefficient for the interaction term between *Non-refund* and *Adv Booking* is not significantly different from zero (as in Table 3). This result is consistent with the use of refundable and non-refundable pricing options to screen consumers and exploit frictions in the transparent market.[44] For example, imagine that a subset of business-travelers (high valuations and high demand uncertainty) are required by their companies to always buy refundable hotel rooms. In this extreme case, hotels might choose to set the refundable premium constant over time to extract surplus from this subset of customers.[45]

Anticipating a booking by one week is associated with *higher* transparent and opaque rates (0.9 and 1.2 percent respectively). As Figure 5 in Appendix A shows, hotel rates patterns behave similarly as the booking date approaches the check-in date. The symmetric effect of early bookings explains the small effect of *Adv Booking* on opaque discounts. We link the positive and symmetric estimated coefficients for *AdvBook* to traditional peak-load pricing strategies that are not related to demand segmentation. Again, we do not find evidence of price discrimination based on weekend/weekday check-in dates. This is somewhat a surprising result since it is commonly assumed to be an important dimension exploited by the travel industry to segment leisure and business travelers. As we argued before, it is quite possible that hotels do not need to price discriminate within each platform if the existence of opaque channels allows the screening of such consumers.

[43] As with the discount equation estimation, we found no evidence of non-linear effects of star-ratings on transparent or opaque prices.

[44] Escobari and Jindapon (2012) present a model that introduces the possibility of price discrimination through refundable and non-refundable rates. They also show that refundable and non-refundable airfares converge over time. Watanabe and Moon (2013) link refundable premiums and price discrimination in the airline industry exploiting cross-section variation across markets.

[45] Alternative, assume that demand uncertainty and consumer's willingness to pay are positively correlated and, that consumers' uncertainty is constant and only resolved at the very last minute.

Table 5: Price Regressions. Opaque Bookings
Dependent variable: $\ln p_j^o$

	(1)	(2)	(3)	(4)
Platform (Hotwire=1)	0.135***	0.128***	0.126***	0.145***
	(0.017)	(0.016)	(0.016)	(0.016)
Chain	-0.002	0.001	0.005	0.000
	(0.024)	(0.023)	(0.022)	(0.024)
Stars	0.301***	0.282***	0.266***	0.239***
	(0.024)	(0.026)	(0.027)	(0.029)
Airport = 1	-0.235***	-0.234***	-0.195***	-0.211***
	(0.030)	(0.030)	(0.029)	(0.030)
Weekend		-0.172*	-0.165*	-0.012
		(0.076)	(0.076)	(0.081)
Wknd*Stars		0.049*	0.048*	-0.004
		(0.021)	(0.021)	(0.022)
Adv Booking (wks)		0.015***	0.013***	0.015***
		(0.003)	(0.003)	(0.003)
AdvBook^2		-0.001***	-0.000***	-0.001**
		(0.000)	(0.000)	(0.000)
SPI		0.005***	0.005***	0.008***
		(0.001)	(0.001)	(0.001)
Area size (sqmi)			-0.002**	-0.002
			(0.001)	(0.001)
Dispersion=Var(distance)			0.012	-0.003
			(0.011)	(0.011)
Comp 0.5mi			0.003***	0.005**
			(0.001)	(0.002)
Constant	2.999***	2.924***	2.959***	3.000***
	(0.088)	(0.101)	(0.107)	(0.118)
City fixed effects	Yes	Yes	Yes	Yes
R-squared	0.570	0.582	0.595	0.643
N	3817	3817	3817	3180
Underidentification:				
Kleibergen-Paap rk LM statistic				28.109
Chi-sq (p-val)				0.000
Weak identification:				
Kleibergen-Paap rk Wald F statistic				63.073

Robust standard errors clustered at the hotel level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 2-step GMM with *Comp 5mi* instrumented in Column (4).

As in most markets, prices increase as a response to demand shocks. This effect is expected to be more pronounced in those industries where firms are capacity constrained. Our proxy for demand shock *SPI* reveals a significant positive effect on hotel rates. Interpreting the magnitude of the coefficient is not easy since the exogenous variable is a time and cross-section relative index. One standard deviation increase in *SPI* leads to a 17% increase in hotel room rates. The effect is symmetric across platforms , explaining the null effect of SPI on discounts.

Last, we report the effects of market characteristics on hotel rates. The airport dummy and the number of hotels within half a mile walking distance capture how product differentiation and number of hotels affect prices. Note first that opaque and transparent rates drop by 16.2 and 14.6 percent in hotels near airports. Aside from hotel quality, customers looking for a room at the airport are usually less concerned about hotel attributes. Moreover, horizontal differentiation by hotels in these markets is less pronounced than in other parts of the city. We should therefore expect tighter competition in the transparent market that pushes down rates in the opaque market.

We find little or none effect of the number of hotels (*comp 0.5mi*) on hotel rates. An additional hotel in the market does not affect transparent rates and increases opaque rates by almost 0.5%. Surprisingly, the coefficients in column (4) are larger once we instrument the number of firms with the office rent per square feet. Two explanations are possible. First, this could be evidence of agglomeration economies, as suggested by (Kalnins, 2006, p.210). Second, there is the possibility that our instrument is correlated with some local market unobservables not captured by the city fixed-effects and the other covariates. Note however that we are mainly interested on the relative impact of competition on opaque rates. Thus, even if the competition coefficient on each price equation is biased, their difference is not.

The number of hotels can have two effects on opaque rates. On the one hand, more hotels mean more competition in the wholesale market and therefore lower cost for the intermediary. This effect is present in the transparent market although, since product differentiation is absent in the opaque market, competition takes a very different shape in the reverse auction. On the other hand, more hotels on a given area can increase or decrease expected utility for opaque channel users. This latter effect depends on the particular consumer preference. In terms of a location model of product differentiation, more hotels in a Hotelling line can increases or decreases the expected utility of buying opaque depending on the assumption of the transportation cost. The results from column (4) indicate that opaque rates are higher in areas with more hotels. The coefficient is very small and therefore not significantly different from zero in the estimation of the discount equation. The variables associated with opacity level (area size and dispersion) in Table 5 are not significant and present a puzzle to our theoretical predictions. More importantly, we would expect bookings in larger opaque areas to be associated with more uncertainty and therefore a lower opaque price. Taken together, our findings suggest that consumers require a large discount to be willing to buy a lottery instead of a known product. However, conditional on buying opaque, these consumers are not very sensitive to the opacity level. In other words, variables that affect the distribution of probabilities over the likely outcomes do not change consumers' willingness to pay.

4.3 Who sells opaque?

We argued above that observed hotel rates induce heterogeneous consumers to self-select across selling channels based on their preferences and transaction costs. We now examine the extent of hotel selection in the opaque channels. A common belief among users of opaque platforms is that, given the area-quality selected, a buyer is more likely to be assigned to a lower-than-average quality hotel. That is, the underlying lottery in an opaque booking encompasses non-uniform probabilities "biased" toward inferior hotels. On the other hand, it can be argued that hotels using the opaque market to segment demand will increase their prices in the transparent market relative to those that are not using the opaque channel Fay (2008). In other words, we should expect that conditionally on selling in the opaque market, a hotel will charge a higher price in the transparent market. We can test these hypothesis since, for each opaque booking, we also observe the transparent rates posted by all hotels of similar quality in the relevant opaque area. More generally, we use this information from the transparent market to study the characteristics of the hotels that sell opaque.

In principle, each opaque booking involves a reverse auction in the back-end among all hotels that satisfy a customer's request (opaque area and hotel quality) where only the winning hotel is disclosed to the buyer. That is, for each opaque transaction $i = \{1, 2, ..., N\}$ in our data, we expect the opaque platform to select the hotel willing to rent a room at the lowest rate. Let

$$B_{ij} = -\alpha_i - b_{ij} = -\alpha_i - (x_{ij}\beta + v_j)$$

represent the rate submitted by hotel j to serve buyer i where α_i represents market-specific shock and x_{ij} captures a hotel's opportunity cost of selling a room in future dates and alternative selling channels. That is, a hotel that does not expect to be capacity constrained by the check-in date is more likely to submit a lower bid to the opaque platform. On the other hand, a hotel close to capacity faces a higher opportunity cost and would be willing to sell opaque only if compensated accordingly (higher B_{ij}). Market wide shocks to demand or supply should only alter the level of the bids while hotel specific shocks are relevant to identify the auction winner. We use different covariates that proxy the value of a room opportunity cost for each hotel at a given point in time. Additionally, we assume that unobservables v_j are drawn from a Type I extreme value distribution. The probability that hotel $h \in J_i$ is selected by the opaque intermediary is therefore given by

$$\Pr(y_{ih} = 1) = \Pr(B_{ih} < B_{ij}) = \Pr(b_{ih} > b_{ij}) = \frac{\exp(x_{ih}\beta)}{\sum_{j=1}^{J_i} \exp(x_{ij}\beta)}. \tag{5}$$

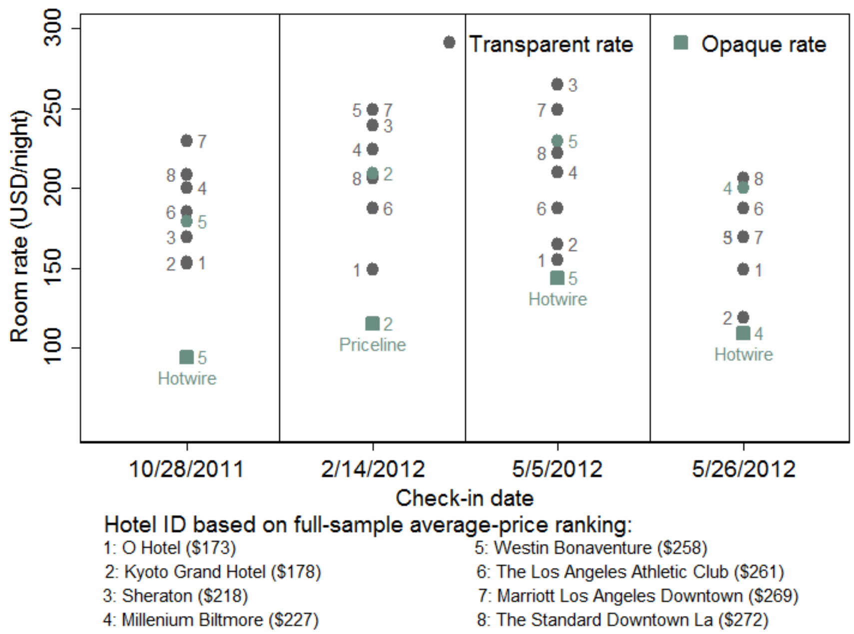
We estimate this probability with a conditional logit regression can be estimated using conditional logit (McFadden, 1974) using different specifications. To illustrate the data used and the variation in our covariates we show in Figure 5 a snapshot of four opaque bookings made with 3.5-star hotels in Downtown Los Angeles. For each booking, the figure displays the opaque rate and channel used together with the transparent rates set by all hotels in the market. Hotels' ids are also displayed and they match the within-market ranking of hotels based on the average price in the full-sample (1=lowest price). For example, the opaque booking with check-in date 10/28/2011 is one of the bookings supplied by The Westin Bonaventure Hotel displayed in Figure 2. The Westin hotel ranks fifth among the eight 3.5-star hotels in Downtown Los Angeles. However, its price for a night on October 28th was relatively cheaper (third).[46]

Controlling for opaque area and star-rating, a hotel ranking based on the full-sample average price reflects within-market variation in quality that is not captured by the discrete star-rating system. Moreover, rankings based on the prices charged by competitors in a given date reflect both, quality differences and the hotel idiosyncratic opportunity cost for a room. The four cases in Figure 2 reveal general patterns present in the data. First, price dispersion varies over time. Second, hotels' price-ordering is not constant although some correlation with the full-sample ranking is present. These two effects combined suggest that hotels experience significant idiosyncratic shocks

[46] As with the matching of transparent and opaque rates in the previous section, the booking date, length of stay and room type is also controlled for.

in demand. Last, the transparent rate charge by the opaque booking provider can be located anywhere in the distribution of transparent prices.

Figure 5: Data snapshot
Four examples from 3.5 star hotels in Downtown–Los Angeles



Note: The cases displayed are a subset of the 41 opaque bookings made by 3.5 star hotels in the Downtown–Los Angeles opaque area. For each opaque booking, the opaque and transparent rates are displayed together with hotels' id which matches the overall price-ranking in our database (1 = lowest price). For example, the first opaque booking (check-in date: Oct 28, 2011) was done by the Westin Bonaventure, a hotel that in our dataset ranks 5th among the eight 3.5 star hotels in Downtown–LA.

Results for markets with 4 to 9 competitors are reported in Table 6. Column (1) shows how hotel h's current rank in the transparent market (1=cheapest rate) impacts the probability of selling opaque. The coefficients are expressed relative to the baseline category ($\text{Rank}_t = 1$) and, except for the case of $\text{Rank}_t = 2$, hotels charging higher transparent rates are less likely to be the providers of the opaque booking. Columns (2) and (3) show a similar picture if we estimate equation 4.3 separately for Hotwire and Priceline. In column (4), we include the full-sample ranking as a covariate to control for the within market variance in quality. The coefficient is significant and positive indicating that hotels of higher quality (i.e., higher average prices) are more likely to sell in the opaque market. Note that the coefficients for the $Rank_t$ remain similar to those in column (1). That is, it is more likely that the hotel assigned in an opaque booking is currently renting rooms at a low price in the transparent market. However, the low transparent rates are due to temporal idiosyncratic shocks and not associated with a hotel being of lower-than-average quality.

The ranking variables $Rank_t$ and $Rank$ aggregate information related to the current and average prices by hotels in a given market. These are discrete variables that do not reflect the size of price differences between hotels. Moreover, since our markets vary from 4 to 9 hotels, the domain for each variable differs across markets and the results in columns (1)-(4) might mask some relationships that are present in large markets but not in markets with few hotels. In column (6) we introduce continuous variables that normalize ranking and prices in the zero-one interval. The variables RR_j and RR_{jt} takes a value of zero and one if the corresponding price ranking for hotel j is one or J_i. Similarly, we define $RP_{jt} = (p^{\tau}_{jt} - \underline{p}^{\tau}_{i})/(\overline{p}^{\tau}_{i} - \underline{p}^{\tau}_{i})$ where $\underline{p}^{\tau}_{i}$ and $\overline{p}^{\tau}_{i}$ are the lowest and highest transparent rates associated with a given opaque booking i. While RR_{jt} can only take equidistant values, RP_{jt} can take any value in the unit line. Results in Column (5) indicate that, holding constant the absolute price rankings, a higher "relative price" reduces the probability of selling opaque further. Last, the specification in column (6) incorporates the three normalized variables reflecting relative rankings and prices. While all coefficients preserve the signs consistent with the results in previous specifications, only the coefficient for RR_t is significant.

The main message from Table 6 is that the current transparent rate charged by a hotel in a given quality-area market is a good predictor of the probability of such hotel serving an opaque booking. Hotels facing a low opportunity cost for a room (low demand relative to capacity) sell at cheaper rates in all channels. Thus, the likelihood of winning the reverse auction implemented by the opaque platform increases. We also reject the idea that hotels that underprice competitors systematically are more likely to sell opaque. We interpret these results as partially reconciling the theories that emphasize the role of the opaque channel to sell unsold inventory with those that identify the price discrimination role. On any given date (e.g., three weeks before check-in) a hotel might find that the current inventory is above the expected threshold. As a consequence it lowers rates across the board and chances of selling opaque increase. The main difference with the prediction from Jerath et al. (2010) is that the hotel does not wait until the last minute to do so.

5 Conclusions

We used a unique dataset with opaque transactions to document stylized facts and provide insights on the economics of opaque selling. Our results are consistent with hotels using selling channels to segment their demand based on consumers' preferences

Table 6: Conditional Logit Estimates
Dependent variable: Pr(sell opaque) = $\Pr(y_{ih} = 1)$

	(1)	Hotwire (2)	Priceline (3)	(4)	(5)	(6)
Rank_t :						
=2	-0.015	-0.049	0.000	-0.038		
	(0.065)	(0.118)	(0.078)	(0.065)		
=3	-0.232***	-0.336**	-0.188*	-0.275***		
	(0.069)	(0.128)	(0.082)	(0.070)		
=4	-0.455***	-0.513***	-0.430***	-0.525***		
	(0.073)	(0.135)	(0.087)	(0.078)		
=5	-0.608***	-0.557***	-0.636***	-0.707***		
	(0.090)	(0.154)	(0.110)	(0.098)		
=6	-0.808***	-0.816***	-0.807***	-0.923***		
	(0.117)	(0.201)	(0.144)	(0.124)		
=7	-0.928***	-1.291***	-0.784***	-1.084***		
	(0.142)	(0.285)	(0.164)	(0.154)		
=8	-0.714***	-1.645***	-0.466*	-0.883***		
	(0.171)	(0.462)	(0.186)	(0.179)		
=9	-1.042**	-1.487*	-0.822	-1.226**		
	(0.392)	(0.727)	(0.467)	(0.396)		
Rank_t					-0.112***	
					(0.027)	
Rank				0.045**	0.048***	
				(0.014)	(0.014)	
RP_t					-0.393**	-0.233
					(0.124)	(0.163)
RR_t						-0.642***
						(0.169)
RR						0.147*
						(0.073)
N	11805	3551	8254	11805	11801	11801
Log-L value	-3404.94	-1006.36	-2393.20	-3400.44	-3399.58	-3402.56
Pseudo R^2	0.022	0.032	0.019	0.023	0.023	0.022

Robust standard errors clustered at the market level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $Rank = 1$ if a hotel has the lowest full-sample average transparent price in a given market (area and star rating). $RR = (Rank - 1)/(J_i - 1) \in [0, 1]$ is the normalized rank. RR_t = normalized price-ranking in the transparent market for a given check-in date t. RP_t = normalized price for check-in date t.

over hotel attributes and transaction costs. Demand shocks and advance booking affect pricing strategies symmetrically across platforms suggesting that opaque intermediaries are not used as a last minute resource by hotels. Moreover, there is little evidence of price discrimination within a platform. This is consistent with opaque platforms fully segmenting consumer types and leaving no room for within-platform price discrimination.

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Appendices

A Additional Figures and Tables

Figure 1: Hotwire's Secret Hot Rate

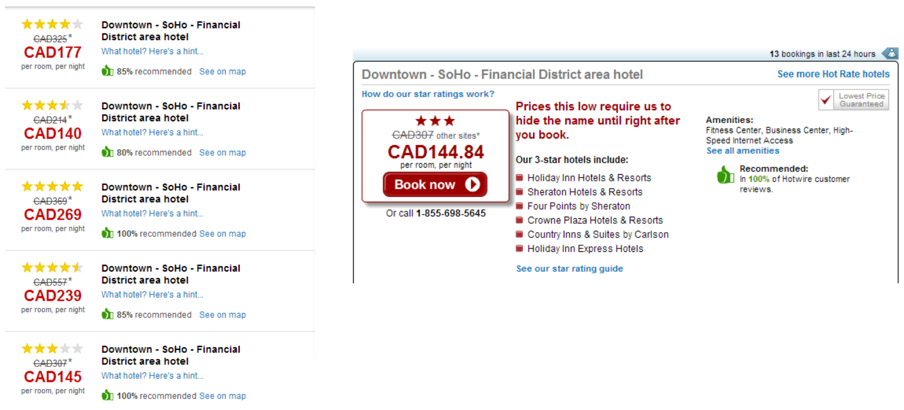


Figure 2: Priceline's Name Your Own Price

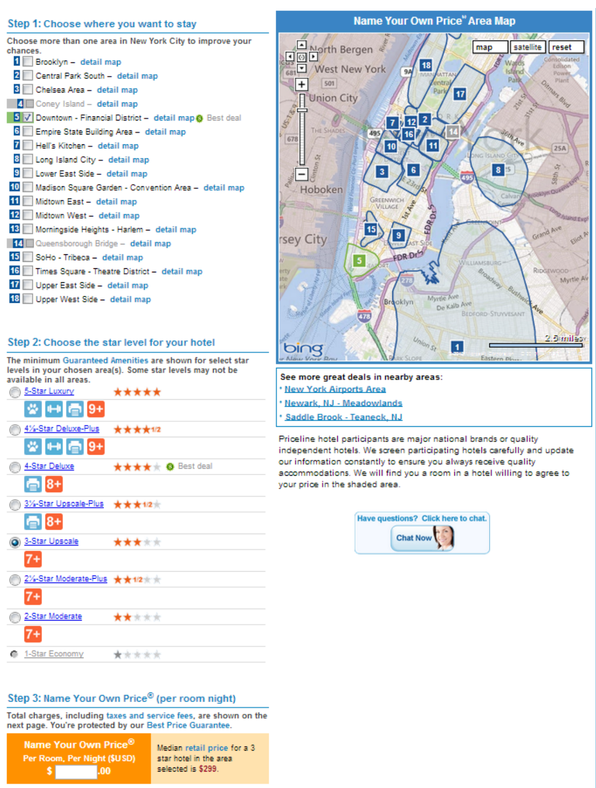
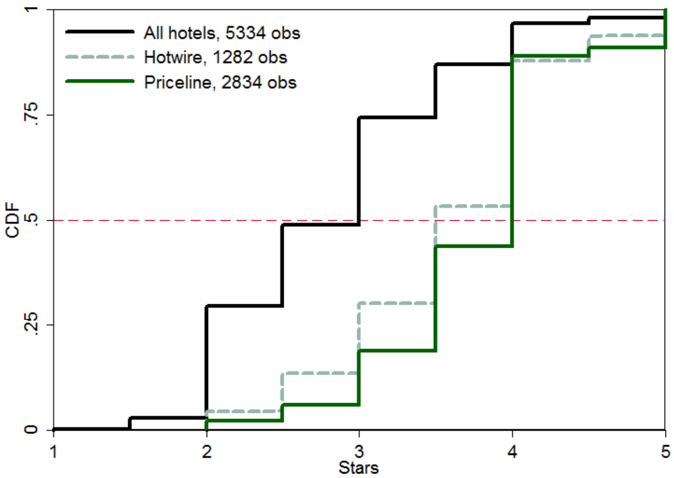
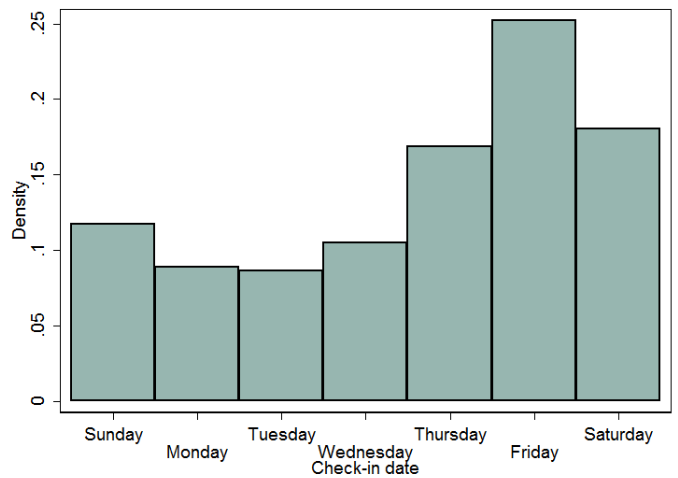


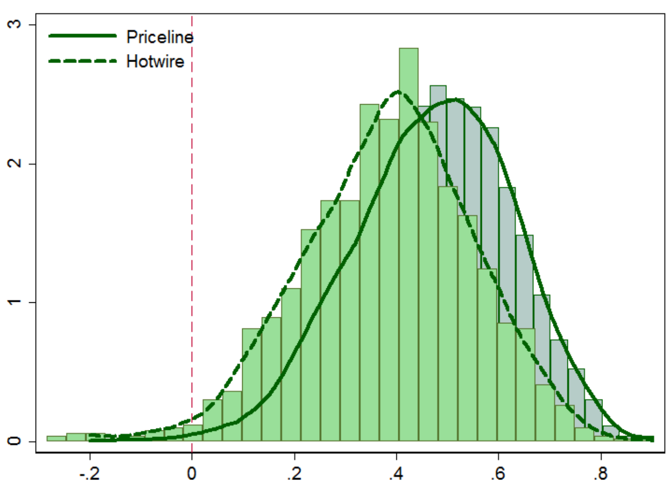
Figure 3: Descriptive Statistics



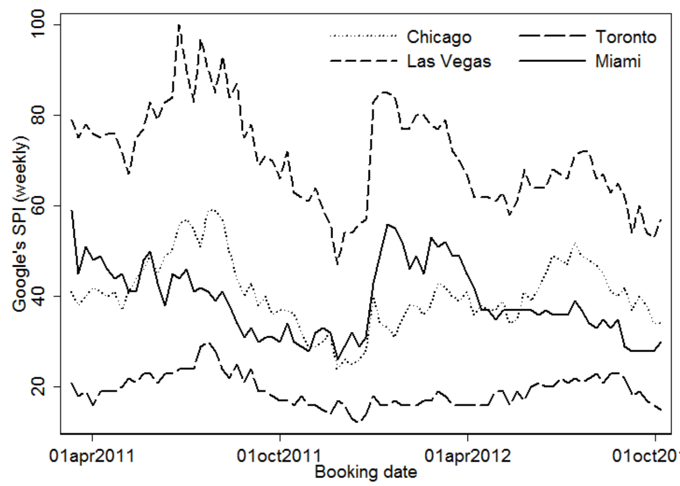
(a) Quality distribution: opaque bookings and hotels



(b) Check-in day of the week



(c) Discounts distribution by platform



(d) Search Popularity Index

Figure 4: Opaque discounts and hotel rates by city

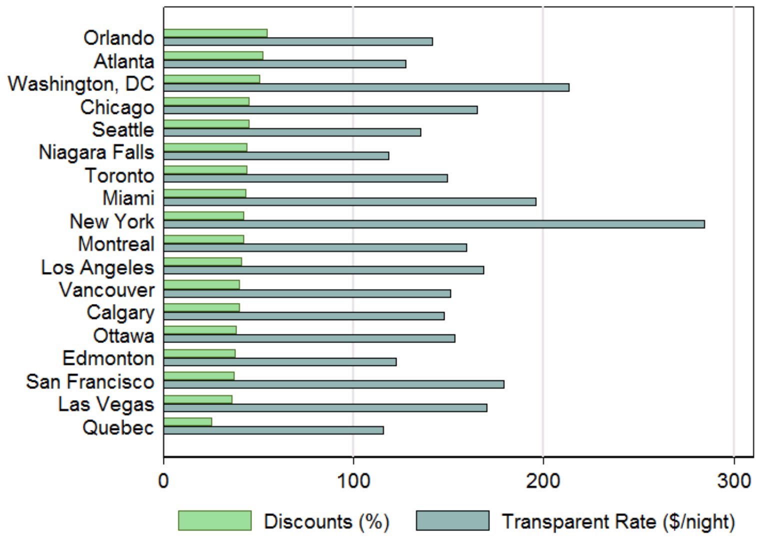
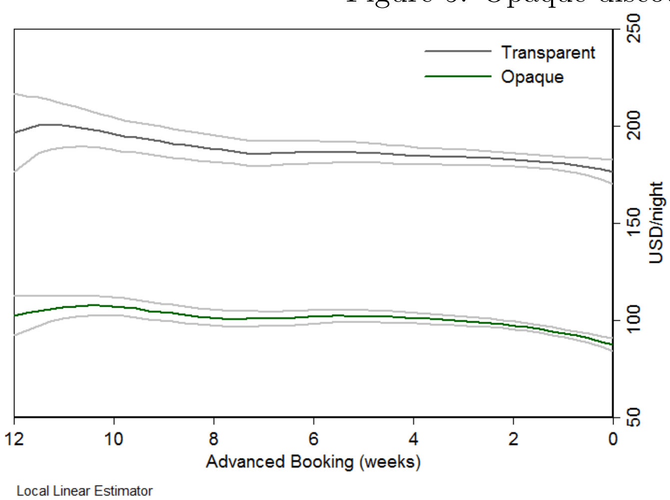
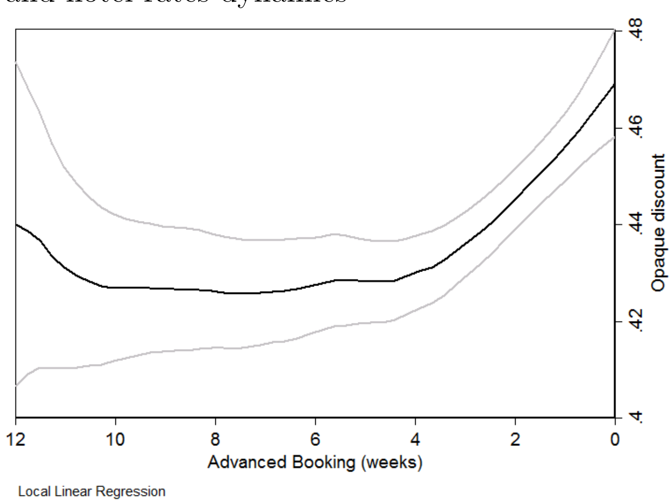


Figure 5: Opaque discounts and hotel rates dynamics

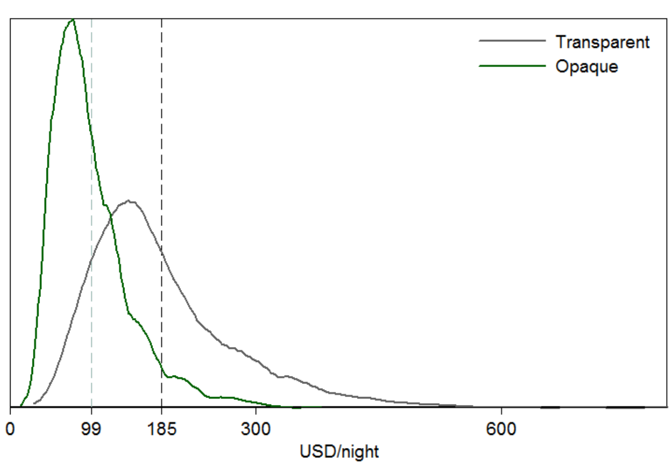


(a) Rates

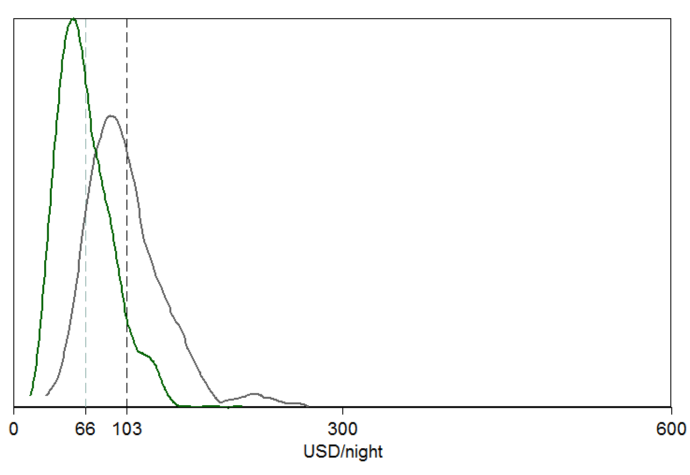


(b) Discounts

Figure 6: Opaque and transparent room rate densities



(a) All observations



(b) Hotels with stars < 3

Table 1: Price Regressions by Platform
Dependent variables: $\ln p_j^\tau$ and $\ln p_j^o$

	All		Hotwire		Priceline	
	$\ln p_j^\tau$	$\ln p_j^o$	$\ln p_j^\tau$	$\ln p_j^o$	$\ln p_j^\tau$	$\ln p_j^o$
	(1)	(2)	(3)	(4)	(5)	(6)
Non–refund	-0.093***		-0.085*		-0.096***	
	(0.023)		(0.033)		(0.026)	
Platform (Hotwire=1)		0.145***				
		(0.016)				
Chain	0.032	0.000	0.054	0.002	0.009	-0.008
	(0.028)	(0.024)	(0.037)	(0.030)	(0.032)	(0.028)
Stars	0.350***	0.239***	0.352***	0.247***	0.337***	0.234***
	(0.024)	(0.029)	(0.035)	(0.038)	(0.031)	(0.037)
Airport = 1	-0.164***	-0.211***	-0.129**	-0.215***	-0.184***	-0.208***
	(0.031)	(0.030)	(0.044)	(0.040)	(0.034)	(0.033)
Weekend	0.004	-0.012	-0.032	-0.085	0.006	0.046
	(0.079)	(0.081)	(0.127)	(0.119)	(0.099)	(0.103)
Wknd*Stars	-0.026	-0.004	-0.018	0.006	-0.026	-0.016
	(0.022)	(0.022)	(0.036)	(0.034)	(0.027)	(0.028)
Adv Booking (wks)	0.009*	0.015***	0.007	0.009	0.012*	0.016***
	(0.004)	(0.003)	(0.006)	(0.005)	(0.005)	(0.004)
AdvBook^2	-0.000	-0.001**	-0.000	-0.000	-0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NonRef*AdvBook	-0.002		-0.002		-0.003	
	(0.003)		(0.004)		(0.003)	
SPI	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Area size (sqmi)		-0.002		0.001		-0.003**
		(0.001)		(0.001)		(0.001)
Dispersion=Var(distance)		-0.003		-0.026		0.006
		(0.011)		(0.021)		(0.011)
Comp 0.5mi	0.003	0.005**	0.007***	0.006**	0.000	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	3.456***	3.000***	3.415***	3.134***	3.529***	3.020***
	(0.092)	(0.118)	(0.152)	(0.163)	(0.111)	(0.147)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.554	0.643	0.563	0.612	0.547	0.659
N	3180	3180	977	977	2203	2203
Underidentification:						
Kleibergen-Paap rk LM statistic	34.659	28.109	31.241	26.157	23.866	18.725
Chi-sq (p-val)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification:						
Kleibergen-Paap rk Wald F statistic	77.546	63.073	69.979	55.230	61.759	48.000

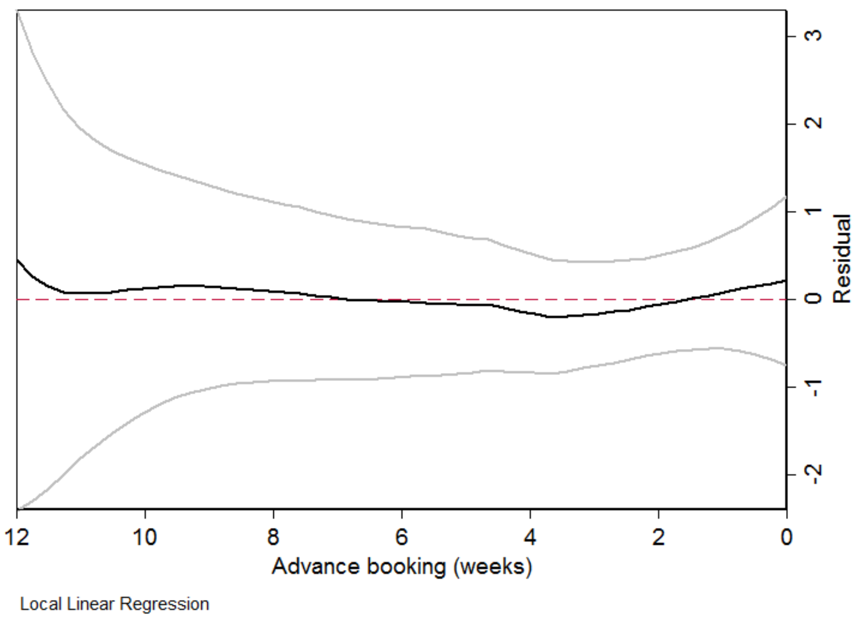
2-step GMM with *Comp 5mi* instrumented in all columns. Robust standard errors clustered at the hotel level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Price Regressions by Platforms (3SLS)
Dependent variables: $\ln p_j^\tau$ and $\ln p_j^o$

	All		Hotwire		Priceline	
	$\ln p_j^\tau$	$\ln p_j^o$	$\ln p_j^\tau$	$\ln p_j^o$	$\ln p_j^\tau$	$\ln p_j^o$
	(1)	(2)	(3)	(4)	(5)	(6)
Non–refund	-0.059***		-0.060*		-0.060***	
	(0.013)		(0.024)		(0.016)	
Platform (Hotwire=1)		0.159***				
		(0.009)				
Chain	0.025	0.004	0.046	0.005	0.004	-0.007
	(0.013)	(0.012)	(0.023)	(0.021)	(0.017)	(0.015)
Stars	0.349***	0.246***	0.352***	0.250***	0.334***	0.243***
	(0.015)	(0.014)	(0.024)	(0.022)	(0.019)	(0.018)
Airport = 1	-0.162***	-0.205***	-0.132***	-0.205***	-0.177***	-0.204***
	(0.019)	(0.017)	(0.038)	(0.036)	(0.021)	(0.019)
Weekend	0.008	-0.010	-0.032	-0.111	0.018	0.062
	(0.073)	(0.067)	(0.114)	(0.108)	(0.097)	(0.087)
Wknd*Stars	-0.027	-0.004	-0.018	0.013	-0.029	-0.020
	(0.020)	(0.018)	(0.032)	(0.030)	(0.026)	(0.024)
Adv Booking (wks)	0.009**	0.014***	0.007	0.009	0.010**	0.016***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
AdvBook^2	-0.000	-0.001***	-0.000	-0.000	-0.000	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NonRef*AdvBook	-0.004		-0.003		-0.005	
	(0.002)		(0.003)		(0.003)	
SPI	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Area size (sqmi)		-0.001**		-0.001		-0.002***
		(0.000)		(0.001)		(0.001)
Dispersion=Var(distance)		0.009		-0.002		0.015*
		(0.005)		(0.009)		(0.006)
Comp 0.5mi	0.003***	0.005***	0.006***	0.006***	0.002	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	3.453***	2.950***	3.415***	3.117***	3.523***	2.965***
	(0.063)	(0.059)	(0.105)	(0.100)	(0.081)	(0.075)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.553	0.641	0.564	0.611	0.548	0.656
N	3180		977		2203	

Generalized Least Squares with *Comp 5mi* instrumented and correlated disturbances across equations. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 7: Advance Bookings and non-linear effects



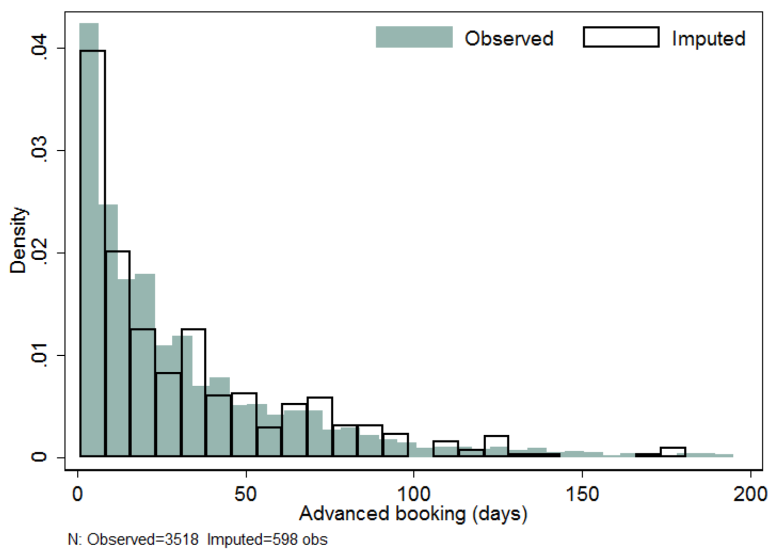
B [Not for publication] Dataset Construction

B.1 Hotel rates

Opaque Data: We collected the opaque bookings from Betterbidding.com. This website has a forum for each city-platform pair where users discuss strategies and report information on successful bookings. Figure 9 shows a snapshot of the Los Angeles–Hotwire forum with 6 different threads. We ignored the "help" related posts and parsed the posts related to successful transactions (i.e. those inside the red boxes). Each one of these post includes a hotel name, opaque area, average rate (net of taxes and fees), check-in date, and length of stay. The users do not report booking dates. However we approximate them with the date the thread was originated.[1]

We dropped observations with booking dates that were made more than 200 days before the check-in date. In many cases (about 14% of the observations), the report dates exceeded the booking date. We performed multiple imputation of booking dates using Stata's ice command and Figure 8 shows the histogram for the observed and the first imputation of advanced booking days. The regressions analysis was done using the first sample of multiple imputation and the complete case sample (i.e. ignoring observations with missing values).

Figure 8: Imputed and observed advance bookings

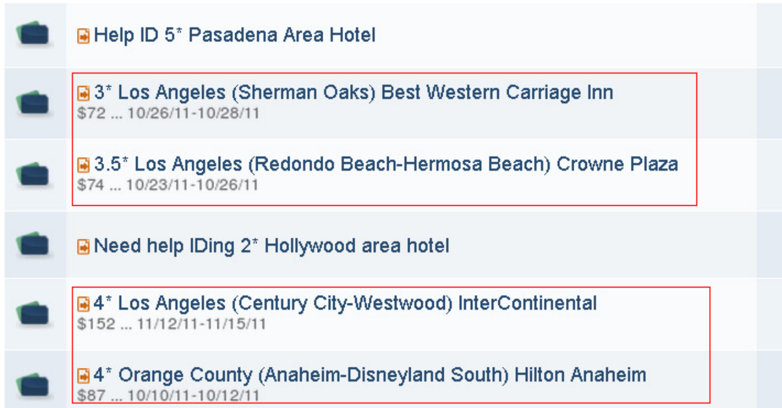


Although hotels price multiresource inventory as the sum of daily rates (Talluri and Van Ryzin, 2005, p. 525), we dropped transactions where the length of stay is over 15 nights because of possible volume discount policies.[2]

[1] Although post dates are not shown in the forum's interface, we can extract it from the html source code.

[2] We analyzed transparent pricing in terms of length of stay (1, 2 and 3 nights) for a sample of 100 hotels in NYC during 6 months and found no evidence of volume discounts. However, it is possible that the additive pricing observed in the transparent market does not apply to opaque bookings.

Figure 9: Betterbidding.com Snapshot: Hotwire–LA Forum



Matching Opaque and Transparent Data: The transparent data from Hotels.com includes hotel room rates for one-night stay only. Thus, to match the opaque transactions with the transparent prices we create an average night rate using all the transparent hotel rates for the length of stay of the opaque transaction. For example, consider the Best Western Carriage Inn booking shown in Figure 9. This 2-night booking was made 14 days before the check-in date for an average rate of $72/night.[3] From the transparent data, the 1-night rates posted by the Best Western Carriage Inn on Oct 12 is $92/night for check-in dates Oct 26 and/or Oct 27 and therefore, the opaque discount for this transaction on Hotwire is 22%.

In some cases, the transparent rate for a given hotel was not available for the same booking and check-in dates of the opaque transaction. In this case, we fix the check-in date and look for the closest booking date for which the hotel posted a transparent rate. The booking dates on half of our matched observations differ by less than 2 days. This difference increases to 13 days in the third quartile of the distribution.

Hotels' quality: Each platform has their own star rating system and they are remarkably similar (possibly due to legal issues). However, since consumers report the name and stars of their hotels, we use Hotels.com rating. In the few cases (22 out of 924) where a hotel changed its rating during the time-frame of our study we use the star rating in place most of the time.

Taxes and Booking Fees: We record opaque and transparent rates net of taxes, fees and commissions. In the case of Hotwire, these are the "base prices" that consumers observe first when searching for deals. Similarly, the opaque rates posted in the Betterbidding.com forum refer to the bids placed on Priceline or the displayed rate by Hotwire.[4] The three platforms collect sales and local taxes. They aggregate taxes with service fees in one line that the buyer observes before confirming a booking. We could not find a statement from each company with the detailed list of taxes and

[3] The post can be seen at http://www.betterbidding.com/index.php?showtopic=144289&

[4] Forum moderators explicitly ask members to post the prices paid before taxes and fees.

Table 3: Opaque transactions matched by cities

City	Obs	Hotels Opaque	Hotels Transparent
Atlanta	162	64	496
Calgary	13	10	85
Chicago	428	116	532
Edmonton	2	2	79
Las Vegas	546	43	194
Los Angeles	274	85	555
Miami	157	68	370
Montreal	71	24	172
New York	660	124	661
Niagara Falls	39	14	168
Orlando	296	70	407
Ottawa	25	10	64
Quebec	5	4	100
San Francisco	240	52	391
Seattle	207	49	253
Toronto	181	47	209
Vancouver	131	31	155
Washington, DC	271	87	444
Total	3,708	900	5,335

Opaque transactions observed in a given city (Column 1) were booked at one of the “opaque hotel” in Column 2. Column 3 reports the total number of hotels in a given city (source: Hotels.com).

processing fees.[5] We have sampled quotes for each city in each platform to asses the relative differences in commissions across platforms. While the average "taxes and fees" charged by `Hotels.com` is around 15%, the opaque platforms add about a 24% to the base rate. Priceline's "taxes and service fees" and Hotwire's "tax recovery charges & fees" average 26% and 22% respectively.

B.2 Hotels and Market characteristics

The transparent data includes rates for 5,335 hotels (924 hotels for which we have opaque transactions) in the 18 cities studied. We collected all characteristics from hotel name, star rating, address, room type. We also calculated walking distances among hotels based on google's driving distance application. Avoiding euclidean distances is important in areas where rivers, highways and airports separate hotels.

B.3 Office rent data

We use the office rent cost to instrument market structure metrics. The source of our office rent data is Jones Lang LaSalle (JLL), a commercial real estate firm. JLL's quarterly "Office Statistics" reports rent values for markets (usually CBD and suburbs) and submarkets in large metropolitan areas.[6] The report displays the asking rent per square foot for offices of three quality levels (A,B and C).

We recorded the asking rent values reported for the third quarter of 2011. Some submarkets report rent values for only two of the three office qualities. Thus, we created three values by recording the highest, lowest and average in each submarket. We then assigned to each hotel a rent value according to JLL's market and sumbarket boundaries and the hotel quality rating: *Rent Max* if *Stars*>3, *Rent Avg* if *Stars*=3 and *Rent Min* if *Stars*<3). Table B.3 shows the summary statistics for the original and transformed rent data.

B.4 Google Trends SPI

Google Trends tracks the search volume for the most popular queries used on Google Search. Google constructs a search popularity index (SPI) for each query by *normalizing* and *scaling* the absolute search activity. We collected the SPI values for queries similar to "hotels in Chicago". First, given the region and time frame specified by the user (e.g.: Worldwide, 2009-2011) the share of the total search volume at each point in time is calculated.[7] The scaling process is an extra step required to compare keywords. Consider the keyword V="hotels in Vancouver" searched *worldwide* between January 2009 and January 2011. Weekly frequency is available therefore

[5] From Priceline's website, "The charge for Taxes and Fees varies based on a number of factors including, without limitation, the amount we pay the hotel and the location of the hotel where you will be staying, and may include profit that we retain".

[6] Las Vegas and Niagara Falls are not included.

[7] The frequency available varies with the popularity of the query.

Table 4: Variables definition

Variable	**Definition**
Transp Rate (p_j^τ)	Transparent rate posted on `Hotels.com`
Opaque Rate (p_j^o)	Opaque rate from Hotwire or Priceline
Discount (D_j)	Rate discount for opaque room $D_j = 1 - p_j^o/p_j^\tau$
Platform	Dummy variable =1 if opaque booking is done on Hotwire (=0 if Priceline)
Adv Booking (wks)	Difference between Check-in and Booking dates (in weeks)
Stars	Hotel quality. Values are $\{2, 2.5, ., 5\}$
Weekend	Dummy variable = 1 if check-in date is Friday or Saturday night or a US–Can Holiday
Chain	Dummy variable for hotels belonging to chains
Non-refund	Dummy variable = 1 if transparent room rate is non-refundable
$SPI_{t,c}$	Google Trends Search Popularity Index for city c and week t (January 2009 – January 2011)
Airport	Dummy variable =1 if opaque area is near airport
Area size	Opaque areas in Figures 11—13 in squared miles
Dispersion	Variance of the walking distance between pairs of hotels located in opaque area
Comp Xmi	Number of hotels within X miles (walking distance)
Comp sim Xmi	Number of hotels within x miles (walking distance)
Comp_same Xmi	Number of hotels of same quality within x miles (walking distance)
Comp_sim Xmi	Number of hotels of similar (± 0.5 star) quality within x miles (walking distance)
Rent X	Asking rent \$psqf by submarket and quality levels $X = \{A, B, C\}$. Source: Jones Lang LaSalle's "Office Statistics" quarterly reports

Table 5: Asking Rent ($ per square foot, 2011Q3)

Variable	N	Mean	SD	Med	Min	Max
Rent A	3,361	39.15	15.63	35.99	2.08	78.86
Rent B	3,422	31.31	10.9	31.34	1.75	53.55
Rent C	1,341	27.84	7.06	27.09	13.47	44.04
Rent Max	3,478	39.02	15.49	35.99	2.08	78.86
Rent Avg	3,478	33.92	12.86	31.64	1.91	66.21
Rent Min	3,478	29.14	10.86	27.06	1.75	53.55

Source: Jones Lang LaSalle, joneslanglasalle.com.

$t = \{1, 2, .., T = 109\}$. Let S_j^V denote the absolute number of V searches on week j. The normalized search index is

$$I_j^V = \frac{100 S_j^V}{\sum_{t=1}^{109} S_t^V}$$

Naturally, I_t^V is bounded by 0 and 100 and reflects variation over time for a search query. When we use city fixed effects, I_t^V represents changes over time in the popularity of the city.

The second step involves scaling the index such that, when the set of keywords searched is larger than one ($V = \{$"$Vancouver$", "$Chicago$", "$LosAngeles$"), only one keyword–week pair gets a score of 100:

$$SPI_j^{V(1)} = I_j^{V(1)} \frac{100}{max\{I_t^V\}} = \left(\frac{S_j^V(1)}{\sum_{t=1}^{109} S_t^{V(1)}} \right) \left(\frac{100}{max\{I_t^V\}} \right)$$

Google trends allows popularity comparisons for different queries at the same time (see Figure 10). All keywords are pooled and the search volumes are normalized by the highest share assuming $t = TxN$ where N is the number of keywords in V. That way, the SPI reveals the relative likelihood of a random search among those keywords.[8] In terms of our data, it captures the fixed effect of a city and its city*time effect. We collected Google Trends data for the period between March 6 2011 and Sept 30 2012.

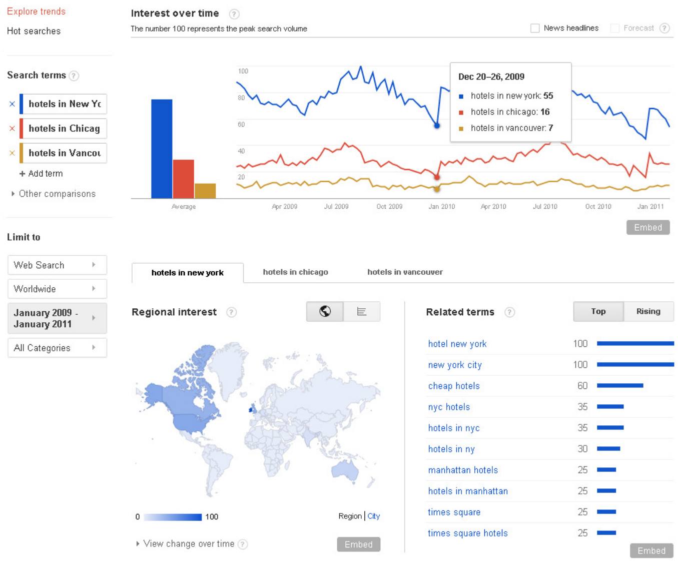
B.5 Market areas by selling platform

We used Priceline's website to replicate and map the opaque areas in each city. Only two of the opaque hotels in our sample did not fall in the areas shown by Priceline on May 2013.[9] We used this information to identify airport areas, and calculate the

[8]When downloading data for many queries at a time, the single keyword index can be recovered by dividing a week's score over the max score and multiplying by 100.

[9]Since the area definitions could have changed from 2012, we allocated these hotels to the closest areas.

Figure 10: Google Trends' snapshot



weighted centroid and size for each opaque area.[10]

[10]We did the same process for Hotwire areas in Los Angeles. The area boundaries almost identical to Priceline's and only the name given by each platform differs.