Online Intermediaries, Prices, and Survival: A Study of OpenTable and New York City Restaurants

Cristobal Cheyre[1] & Alessandro Acquisti[2]

Heinz College, Carnegie Mellon University

Preliminary Draft

Please do not Circulate/Quote without Authors' Permission

Date of this Version: September 2018

Abstract

In recent years, several online platforms have emerged across different industries to mediate previously direct business-to-consumer transactions. Examples include Uber, Airbnb, and OpenTable. These platforms transform legacy industries in two ways: They leverage data and connectivity to reduce costs related to search, replication, transportation, tracking, and verification. They also act as two-sided markets, introducing network dynamics to otherwise traditional industries, which gives substantial market power to intermediaries. We use the case of OpenTable (an online restaurant reservation platform) to investigate how the rise of digital intermediaries affects legacy players in an industry. We develop a model to predict restaurants' adoption decisions and the effect of adoption on prices, profits, and consumer surplus. As long as OT can be used to poach customers from competitors, the adoption decision can be configured as a prisoner's dilemma for a restaurant. Restaurants join the platform to attract customers from competitors or to protect their clientele from adopters. Even assuming a scenario where OT has no effect on expanding aggregate demand, and thus restaurant couldn't expect to attract additional customers by joining the platform, all restaurants would still have incentives to join to protect their clientele. Our model predicts that increasing adoption leads to higher prices, as restaurant pass down the costs of the platform to diners through price, and has no effect on profits. To test these predictions, we compile a dataset containing prices, survival, and OpenTable participation for over 6,000 restaurants in NYC between 2005 and 2016. Our empirical analysis confirms the predictions of the model. Adoption by competitors influences a restaurant's adoption decision; restaurants that join the platform raise prices more than other restaurants, even after controlling for factors that may simultaneously affect adoption and prices; and, over the long-term, participating in OT doesn't seem to increase the likelihood of business survival.

[1] ccheyre@cmu.edu

[2] acquisti@cmu.edu

1 Introduction

In recent years, we have witnessed the migration of traditionally offline arm-length transactions to the online world, where business-to-consumer transactions become mediated by digital platforms. These new services are offered by innovators that carve roles for themselves as intermediaries in previously direct transactions, or that have devised alternative means of providing existing services. Uber and Lyft have done so for personal transportation, Airbnb for lodging, and OpenTable for restaurant reservations. Advocates of these technologies portray them as innovations with the potential of benefitting the various parties that participate in them. Thanks to data analytics and connectivity, these services may unlock excess capacity of shareable goods and put them to work (Benkler 2004; Lobel 2016), allow for flexible arrangements of employment (Chen et al. 2017; Rosenblat 2016; Hall and Kruger 2016), and ultimately can generate new gains from trade (Fariberger and Sundararajan 2015) and increase consumer surplus (Cohen et al. 2016). Incumbents in the industries being disrupted do not hold such positive views. Critics contend that these platforms generate profits by engaging in regulatory arbitrage (Tomasetti 2016; Pollman and Barry 2016) and use technology to redefine employment relationships to their advantage (Rosenblat and Stark 2016; Berger et al. 2018; Cherry 2016).

As online platforms become the central marketplaces in several industries, understanding the benefits they create, what are the underlying economic mechanisms of those gains, and how they are distributed among different stakeholders becomes increasingly relevant. The changes brought upon by the emergence of online intermediaries depend on the interplay of two forces. From one side, the digital nature of online intermediaries may alleviate market imperfections and create new gains from trade by reducing costs related to search, replication, transportation, tracking, and verification (Goldfarb and Tucker, 2017). From the other side, these innovations are often two-sided markets, where intermediaries yield significant power on how transactions occur (Calo and Rosenblat, 2017). Two-sided markets are characterized by the existence of externalities between the parties participating in them, and the inability of those parties to negotiate away these benefits/costs (Rochet and Tirole; 2003, 2006). A common concern of this literature is how the price structure imposed by the platform affects participation (Edelman and Wright, 2015a), and how pricing conditions may lead to overuse of the platform, which results in an increase in retail prices and an overinvestment in (sometimes wasteful) consumers' benefit (Edelman and Wright, 2015b). To determine the net effect of the introduction of online intermediary platforms, it is necessary to simultaneously consider the potential efficiency gains created by technology, along with how stakeholders' actions are influenced by the incentives introduced by platforms.

In this paper, we highlight the importance of platform design by studying how an intermediary platform that charges sellers and subsidizes buyers may be adopted by sellers even if in the long-term they would get no benefits from participating in it. We first develop an analytical model to explain the adoption decision and the consequences it has for prices, profits, and consumer surplus. We then test how the predictions of our model

compare to the outcomes experienced by restaurant and diners after the introduction of online reservation platforms. To do so, we compile a dataset containing prices, survival, and OpenTable (OT) participation for over 6,000 restaurants in New York City (NYC) between 2005 and 2016. The restaurant industry in NYC and OT provides expedient setup for our study for several reasons. First and foremost, OT is a relatively "clean" example of an innovator getting in between a relation that was previously established by other means: With OT, little has changed in the restaurant industry besides a new system for making reservations. Secondly, OT is a long-lived service that was created before the dot-com bubble and that achieved high adoption rates over time.[3] Finally, the restaurant industry is an important part of NYC's economic activity and there is plenty of information to leverage for our study. According to the National Restaurant Associations (2018), restaurants in New York accounted for 9% of employment in the state and had sales of $43.3 billion in 2017. Over half of restaurants in the state are located in NYC. We use information from NYC's department of health and mental health (DOHMH) to identify all active restaurants in the city, as well as annual surveys on a select number of restaurants published by Zagat to obtain prices. Participation of restaurants in OT is obtained from historical snapshots of the platform's website stored in the Internet Wayback Machine.

We model OT adoption as a form of Hotelling competition with differentiated goods. Restaurateurs must choose whether to adopt an innovation that, for an increase in marginal cost, offer customers additional utility. The key prediction of the model is that a prisoner's dilemma arises when adopting the technology allows restaurants to poach customers from competitors. All restaurants have incentives to join the platform to steal clients from competitors, or to protect its clientele from adopters. Even if we assume OT has no effect on expanding aggregate demand, and restaurants cannot expect to attract additional customers by joining the platform, all restaurants would still have incentives to join to protect their clientele. As we show in the discussion section, this is not a farfetched assumption. While OT achieved remarkable adoption rates in NYC between 2008 and 2017, the restaurant industry in the city grew slower than the industry in the rest of the country, and slower than other industries in New York. Under this assumption, our model predicts that increasing adoption leads to higher prices and has no effect on profits.

A hurdle for our empirical analysis is that the decision to join OpenTable is endogenous and likely correlated with our dependent variables. It is reasonable to expect that higher quality restaurants are more likely to adopt an innovation that enhances diners' experience, and at the same time those restaurants are more likely to command higher prices and have better survival chances. To account for this, we employ three different strategies. We first take advantage of the 12 years of panel data we compiled on restaurant prices and OT adoption to implement a difference-in-difference analysis. This approach does not entirely eliminate the

[3] OpenTable was founded in 1998. In mid-2014 it was acquired by the Priceline Group Inc. in an all cash offer valued at US$2.6 billions. Currently the platform serves over 40,000 restaurants in 20 countries.

endogeneity concerns, as it cannot account for time-varying variables that simultaneously influence restaurants' likelihood of adopting OT, and restaurants' prices. Thus, to account time-varying characteristics that influence self-selection, we use a Heckman-style endogenous treatment effect model. As exclusion condition, we use the OT adoption rate by neighboring restaurants that serve food in a different cuisine. We expect adoption by this group of restaurants to influence adoption by increasing awareness about the platform, but not to influence demand and prices, as competition between restaurants in different (broadly defined) cuisines is moderate. The last strategy is based on the observation that what really drives price increase is not OT adoption per se, but the fraction of guests that use OT to make their reservations. While the adoption decision is endogenous, restaurants have little control over how guests make reservations. Thus, relating price increases with the fraction of guests that use OT to make reservations is less affected by endogeneity. To obtain a proxy for the fraction of guests that use OT we collect information on the number of reviews received by restaurants on OT and Yelp. Throughout the different specifications, we find that as OT adoption increases, the cost of the platform is passed down to diners through price. We find no evidence of OT participation having a significant effect on increasing the likelihood of survival of adopters.

This work is related to prior research on the effects of digital markets on search and matching, and to an emerging literature on the economic impacts of online platforms on participants and on displaced incumbents. A rich literature has examined how the reduction of search costs introduced by digital markets affects prices (Brynjolfosson and Smith, 2000; Brown and Goolsbee, 2002; Zettelmeyer and Silva-Risso, 2001; Orlov, 2001), brand differentiation (Waldfogel and Chen, 2006), and product variety (Yang, 2013; Anderson, 2006; Bryjonlfsson et al. 2011). This literature finds that online markets introduce downward pressure on prices, create opportunities for brands to highlight unique attributes, and increase the availability of niche products. More recent research has analyzed how online platforms facilitate matching, and how they affect legacy markets. For example, Zervas et al. (2017) show how AirBnb allows supply of accommodations to enter the market quickly during periods of peak demand. They also show the platform has had a negative impact on hotels' revenues and occupancy rates in the state of Texas. Others have shown how the introduction of Craigslists caused a sharp drop on sales of classified ads by traditional newspapers (Kroft and Pope 2014; Seamans and Zhu 2014) and had a positive effect on decreasing rental and home vacancies (Kroft and Pope 2014). We contribute to this literature by showing how the adoption of OT has affected restaurants and diners in NYC.

Our paper is also related to research that has examined competition and pricing strategies in two-sided markets. A common concern of this literature has been how intermediaries may manipulate demand to increase use of their services, and thus their profits. Several works have studied how credit card rewards programs may lead to excessive use of such cards and introduce distortions in goods and services' prices. The key argument is that the use of credit cards is costly for merchants, which creates incentives for them to increase prices to recover the fees paid in credit card interchange fees (Prager et al. 2009). This results in complex re-distributional

dynamics between those who benefit from the existence of credit cards reward programs (Hayashi 2009), and those who end up paying for those benefits (Schuh et al. 2010). Rysman and Wright (2014) provide a review of theoretical contributions on interchange fees in credit cards and discuss how they can inform public policy. Testing the prescriptions of this literature empirically is difficult. The vast nature of credit card usage and payment networks makes collecting representative information on merchants, credit card users, credit card issuers, and banks interchange fees unfeasible. However, credit cards are not the only intermediaries where this problem arises. Edelman and Wright (2015a) argue a key feature of credit cards is that they enforce price coherence, which means that sellers cannot charge a different price to buyers that use credit cards. They provide several examples of other intermediaries where this rule applies. In a theoretical contribution, Edelman and Wright (2015b) show how an intermediary that enforces price coherence can profitably increase demand for its services, which leads to increased prices, excessive use of the intermediaries' service, over-investment in benefits to buyers, and could lead to reduced consumer surplus. We contribute to this literature by providing empirical evidence of how the adoption of an intermediary that operates under price coherence has led to price inflation, and discuss how the platform has affected sellers' profits and consumer surplus.

Our analytical model and empirical results highlight the importance of understanding the tradeoffs between the gains generated by analytics and connectivity in online platforms and the distortions that may be introduced by the platforms' design. Our analysis of OT suggests that, even though the platform is free for diners to use, in the long term they end up paying for the costs of the platform through price increases. This doesn't mean that the platform is welfare destroying, as while diners face higher prices, they also benefit from lower search costs due to the convenience of making reservations online. However, it does imply that the platform's realized benefits and costs may be different from its intended contribution. The paper is organized as follows. In section II we provide a brief description of OT, its evolution over time in NYC, and the opinion of some restaurateurs about the platform. Section III presents our analytical model. Section IV describes our data and empirical strategy. Section V introduces the empirical results. Finally, in section VI we discuss our findings and provide some remarks regarding the limitations, economics significance, welfare consequences, and broader implications of our results.

2 OpenTable and the Restaurant Industry in New York City

OpenTable was founded in 1998 by Chuck Templeton after he came up with the idea of an online restaurant-reservation service after her wife spent hours on the phone trying to secure a reservation. It consists of an online platform that allows restaurants to manage their bookings using a table management terminal, and lets diners find and secure available tables online. To participate in the platform, under the standard service at the time we study, restaurants paid a setup fee of around US$700 (depending on options selected), a monthly fee of US$250, and a cover fee of US$1 per guest. Restaurants participating in OT can choose the number of

tables they make available for booking online. For diners, using the platform to make reservations is free. In addition, diners receive rewards for completed reservations. Roughly, diners get a US$20 gift certificate (valid for paying at restaurants that participate in OT) every 20 reservations they complete. During its long life, OT has developed loyalty among diners, and while it has attracted open criticism from some restaurateurs, its adoption rate is remarkable. According to data from NYC's DOHMH, in 2014 there were ~24,000 active food establishments in the city, of which ~6,800 were categorized as restaurants with wait service. Figure 1 shows the number of restaurants in NYC participating in OT over time. In the early 2000s, only a couple hundred restaurants participated in the platform, a figure that grew to ~2,000 restaurants by 2014. Considering that not all restaurants accept reservations, having about a third of the restaurants in the city (with wait service) sign up for the platform is notable. Adoption of online reservation systems by diners was also remarkable by 2014. In the 2014 Zagat Survey, 56% of surveyors reported they typically make reservations online (Zagat 2014, pp. 5).

Figure 1: Number of Restaurants in NYC that Participate in OT over Time, by Price Range (Price Ranges as Reported by OT in its website).

To understand the benefits that an online platform provides its users, it is important to contrast the intended value proposition with the realized value. How a platform is used by its adopters will influence whether the proposed contribution materializes or not. The case of OT is telling. Its value proposition for restaurants is to help them fill additional seats. For a restaurant, each seat that goes unused is effectively lost revenue that cannot be recouped. Thus, even though paying a fee to acquire additional guests reduces those customers' profitability, it is better than having empty seats. Intuitively, restaurants that should be more willing to adopt OT are those with higher prices (and presumably higher per-seat net revenue) and those with a lot of unused capacity. Looking at figure 1, the first restaurants to join OT were mid and high range priced establishments. This makes sense, as these are the kind of places that benefit the most from attracting additional clients. However, once adoption reaches a threshold, less expensive restaurants, which conceivably have less to gain

from the platform, start adopting rapidly. To understand what the cause of this trend could be, consider what happens after many restaurants and diners are participating in the platform. While restaurants would prefer to use OT only for seats that usually go unused, diners will always prefer to book through OT as it is more convenient than other alternatives and it gives them rewards. Once enough diners and restaurants have joined the platform, not participating in the platform (or restricting the number of seats available in it) becomes risky. If a potential customer does not find a seat available through the platform, it may just choose a competing restaurant with open seats in OT, instead of attempting to make the reservation by other means. This creates a tension between restaurants and diners, as restaurateurs complain that customers overuse the platform, and that OT does not bring enough additional guests. For example,[4] Anjan Mitra - the proprietor of a popular Indian Restaurant– was quoted by New York Times saying that he paid as much as $50,000 per month to OpenTable and got little additional business from the platform. In his own words: "I don't mind paying OpenTable for new customers, but OpenTable was charging me for customers I already had and knew well."

Criticism against the platform by restaurateurs has been common. In a particularly detailed critique, San Francisco restaurateur Mark Pastore wrote a detailed blog post on his restaurant's webpage on why he thought OT was a poor bargain for restaurant owners. The post gained notoriety and sparked notes on several newspapers, including The New York Times[5]. Pastore's argument is that, initially, the reservation system makes sense for the restaurant. It helps fill up unused capacity, and while the per table margin on the tables booked via the service will be lower due to the fee, it is still better than having empty tables. The problem arises when OT starts taking up reservations that were previously done through other means (typically over the phone with little to no added cost to the restaurant). Once most reservations start coming through OT, fees add up to tens of thousands of dollars a year and the restaurant's profitability is significantly affected. At that point, even though the restauranteur starts resenting the fees, he feels locked into the platform as he fears losing most of his clientele if he parts ways with OT.

3 A Model of OpenTable Adoption and its Effects for Restaurants and Diners.

In this section we present a simple two restaurants model to explain a restaurant's OT adoption decision, the response of its competitor, and the implications that adoption of the platform has over prices, profits, and consumer surplus. Our model is not focused on considering different types network externalities in multi-sided platforms, and instead takes as given the participation and price structure used by OT. Rochet and Tirole (2006) and Armstrong (2005) provide comprehensive theoretical models that account for usage externalities and/or membership externalities under different settings. We also don't attempt to demonstrate

[4] https://www.nytimes.com/2017/08/29/dining/opentable-restaurant-reservations.html

[5] http://www.nytimes.com/2010/12/12/business/12digi.html.

how price coherence may lead to inflated prices and over use of the platform under different conditions. Edelman and Wright (2015b) provide a detailed account of the implications of price coherence. Our focus is to show how a platform with OT's structure, which is shared by many online intermediaries, may lead sellers to the strategic decision of adopting the platform even under assumptions implying that, in the long term, they cannot expect to gain much from participating in it.

We consider a Hotelling model in which two restaurants (*a* and *b*) serve a continuum unit mass of consumers uniformly distributed over a unit length interval. We normalize the cost of production to zero and assume that restaurants' locations are exogenously given as *l* and *(1-l)*. A consumer that is located at a distance *x* from a restaurant and buys one unit from it, obtains a utility μ and incurs in a transportation cost of tx^2. We assume that μ is high enough that, in all scenarios considered, all consumers buy one unit from one of the two restaurants (in the conclusions section we explain how this restriction can be relaxed, and how it would change the prescriptions of the model). In our model, we interpret the location of a consumer as its preferred variation of restaurant, and the transportation cost as the disutility of consuming a unit different from the preferred variation. If a restaurant charges P_i per unit, then the utility of a consumer located in *x* is:

If buying from restaurant *a*: $U_a = \mu - P_a - t(x - l)^2$

If buying from restaurant *b*: $U_b = \mu - P_b - t(1 - x + l)^2$

We assume both restaurants already exist, are operating in equilibrium, and that relocation is costly. This implies, due to the well-known equilibrium of the Hotelling model with quadratic transportation costs, that each restaurant will be located at one end of the unit length line. Now, assume an innovator offers a technology to restaurants that will increase the utility for its customers by ρ if adopted. The innovator acts as an intermediary and will only increase utility of consumers that buy through it. The restaurant cannot charge a higher price to consumers that use the intermediary, and thus any consumer that is aware of the technology will use it if buying from an adopter. We assume a fraction α of consumers are aware of the intermediary, and that awareness is independent of consumers' location and uniformly distributed across the unit length interval. The provider of this technology is a monopoly platform that sets a price *c* per unit, i.e. restaurants incur in a cost *c* for each consumer that uses the intermediary. At time 1 of the model each restaurant decides whether to adopt the technology or not, and at time 2 of the model each restaurant sets its price P_i and customers choose to buy one unit from their preferred restaurant. In order to find the pure strategies Nash equilibrium of the model, we consider the four possible scenarios and solve by backward induction.

We first consider the scenario in which none of the two restaurants adopts the technology. In this case, which simply corresponds to a standard Hotelling model with quadratic transportation costs, restaurants split the market in half, and each get the same profits. The price, demands, profits, and consumer surplus associated in this scenario are given by:

$$P_a = P_b = t \tag{1}$$

$$X_a = X_b = \frac{1}{2} \tag{2}$$

$$\pi_a = \pi_b = \frac{t}{2} \tag{3}$$

$$CS = v - t - \frac{t}{12} \tag{4}$$

We next consider the scenario in which both restaurants adopt the platform. In this case, we need to distinguish between consumers that are aware of the platforms and those who are not. An informed consumer will be indifferent between buying from restaurant *a* or from restaurant *b* if he is located in the point *x* over the unit length interval that makes the utility of buying from either restaurant the same:

$$\mu + \rho - P_a - tx^2 = \mu + \rho - P_b - t(1-x)^2 \tag{5}$$

All informed customers to the left of *x* buy from restaurant *a*, and all restaurants to the right of x buy from restaurant *b*. As a fraction α of consumers are informed, the demand from informed consumers for each restaurant is given by:

$$X_{Ia} = \alpha\left(\frac{P_b - P_a - t}{2t}\right) \tag{6}$$

$$X_{Ib} = \alpha\left(\frac{P_a - P_b - t}{2t}\right) \tag{7}$$

In the case of uniformed consumers, the indifferent consumer will be located at point *x* defined by:

$$\mu - P_a - tx^2 = \mu - P_b - t(1-x)^2 \tag{8}$$

Following the same reasoning as before, the demand from uninformed consumers for each restaurant is:

$$X_{Ua} = (1-\alpha)\left(\frac{P_b - P_a - t}{2t}\right) \tag{9}$$

$$X_{Ub} = (1-\alpha)\left(\frac{P_a - P_b - t}{2t}\right) \tag{10}$$

To determine the prices that each firm will set in time 2 of the model, we need to consider the firms' profit maximization problem. The price the firm charges to informed and uninformed customers is the same, and for customers who buy through the intermediary, the firm has to pay the platform's cost *c*. Thus, the profit function for each restaurant *i* is:

$$\pi_i = (P_i - c)X_{Ii} + P_i X_{Ui} \tag{11}$$

By replacing the demands from equations (6), (7), (8) and (9) in the profit function of each firm described by (11), and then solving the maximization problem we obtain:

$$P_a = P_b = t + \alpha c \tag{12}$$

$$X_a = X_b = \frac{1}{2} \tag{13}$$

$$\pi_a = \pi_b = \frac{t}{2} \tag{14}$$

$$CS = \alpha\left(v - t - \frac{t}{12} + \rho - \alpha c\right) + (1-\alpha)\left(v - t - \frac{t}{12} - \alpha c\right) \tag{15}$$

$$CS = v - t - \frac{t}{12} + \alpha(\rho - c) \tag{16}$$

Note that in the full adoption scenario, both restaurants will split the market in half, and will obtain the same profits as in the no adoption scenario. Customers will face higher prices, as restaurants pass down the costs of the platform. The higher the number of customers that know and use the platform (as represented by α), the higher the prices will be. Aggregate consumer surplus will be higher as long as $\rho > c$, i.e. as long as the benefits of the platform are greater than its costs. However, it is interesting to note that informed customers will obtain higher consumer surplus (compared to the no adoption case), while uninformed consumers will obtain lower consumer surplus. This is easy to see in equation (15). The first term of the equation represents the consumer surplus for informed consumers. This will be higher than in the no adoption scenario (given by equation 4), as informed buyers obtain a greater utility thanks to the platform and only pay a fraction of the platform's cost. The second term corresponds to the consumer surplus of uniformed consumers. This is lower than in the no adoption scenario, as uninformed consumers don't obtain the additional utility offered by the platform, but still pay part of the platform's cost.

Proposition 1: Under full adoption, restaurants will raise their prices in an amount equivalent to the costs imposed by the platform.

Proposition 2: Under full adoption, the price increase associated with participating in OT is related to the number of customers that know about and use OT.

Proposition 3: Under full adoption, restaurants will not obtain any profit gains from OT participation

We finally consider the partial adoption scenario. For this case, let's assume that restaurant *a* decides to adopt, while restaurant *b* decides not to (the other case is analogous). The indifferent informed consumer position will now be defined by:

$$\mu + \rho - P_a - tx^2 = \mu - P_b - t(1-x)^2 \tag{17}$$

As before, all consumers to the left of *x* buy from restaurant *a*, while those to the right of *x* buy from restaurant *b*. Thus, the demand each firm face from informed consumers is:

$$X_{Ia} = \alpha\left(\frac{1}{2} + \frac{P_b - P_a}{2t} + \frac{\rho}{2t}\right) \tag{18}$$

$$X_{Ib} = \alpha\left(\frac{1}{2} + \frac{P_a - P_b}{2t} - \frac{\rho}{2t}\right) \tag{19}$$

The demand from uninformed consumers is the same as in the previous case:

$$X_{Ua} = (1-\alpha)\left(\frac{1}{2} + \frac{P_b - P_a}{2t}\right) \tag{20}$$

$$X_{Ub} = (1-\alpha)\left(\frac{1}{2} + \frac{P_a - P_b}{2t}\right) \tag{21}$$

The profit functions for each restaurant are:

$$\pi_a = (P_a - c)X_{Ia} + P_a X_{Ua} = (P_a - c)\alpha\left(\frac{1}{2} + \frac{P_b - P_a}{2t} + \frac{\rho}{2t}\right) + P_a(1-\alpha)\left(\frac{1}{2} + \frac{P_b - P_a}{2t}\right) \tag{22}$$

$$\pi_b = P_b X_{Ib} + P_b X_{Ub} = P_b\,\alpha\left(\frac{1}{2} + \frac{P_a - P_b}{2t} - \frac{\rho}{2t}\right) + P_b(1-\alpha)\left(\frac{1}{2} + \frac{P_a - P_b}{2t}\right) \tag{24}$$

In time period 2 of the model, each firm will choose the price that maximize its profits. We thus obtain:

$$P_a = t + \frac{2}{3}\alpha c + \frac{1}{3}\alpha\rho \tag{25}$$

$$P_b = t + \frac{1}{3}\alpha c - \frac{1}{3}\alpha\rho \tag{26}$$

$$X_a = \frac{1}{2} + \frac{1}{2t}\left(\frac{\alpha\rho}{3} - \frac{\alpha c}{3}\right) \tag{27}$$

$$X_b = \frac{1}{2} - \frac{1}{2t}\left(\frac{\alpha\rho}{3} - \frac{\alpha c}{3}\right) \tag{28}$$

$$\pi_a = \left(t + \frac{2}{3}\alpha c + \frac{1}{3}\alpha\rho\right)\left(\frac{1}{2} + \frac{1}{2t}\left(\frac{\alpha\rho}{3} - \frac{\alpha c}{3}\right)\right) - \alpha c\left(\frac{1}{2} + \frac{\rho}{2t} - \frac{\alpha c + 2\alpha\rho}{6t}\right) \tag{29}$$

$$\pi_b = \left(t + \frac{1}{3}\alpha c - \frac{1}{3}\alpha\rho\right)\left(\frac{1}{2} - \frac{1}{2t}\left(\frac{\alpha\rho}{3} - \frac{\alpha c}{3}\right)\right) \tag{30}$$

In this scenario, as long as $\rho > c$, restaurant *b* has fewer customers and charges a lower price. Thus, it obtains a lower profit than in the other two scenarios. In contrast, restaurant *a* has more customers and is able to charge a higher price. Note that profits for firm *a* will be higher than in the other two scenarios, as the price increase $\left(\frac{2}{3}\alpha c + \frac{1}{3}\alpha\rho\right)$ is greater than the platform's cost (αc), and moreover, the price increase is paid by all customers, while the firm only incurs in the cost increase for the fraction of customers that bought through the platform.

Analyzing the consumer surplus in this scenario is more involved than in the other two cases. To simplify the analysis, let's consider the case where all customers are aware of the platform ($\alpha = 1$). We can obtain the consumer surplus in the full adoption scenario by replacing $\alpha = 1$ in equation 16: $v - t - \frac{t}{12} + \rho - c$. The consumer surplus in the partial adoption scenario is:

$$CS = v - t - \frac{t}{12} + \frac{\rho - c}{2} + \frac{(\rho - c)^2}{36t} \tag{31}$$

The consumer surplus in the partial adoption scenario will be higher than in the no adoption scenario (equation 4), as long as $\rho > c$. The full adoption scenario will provide higher consumer surplus than the partial adoption scenario as long as the difference between the platforms benefits and costs is not a lot more than the transportation costs (or formally as long as $\rho - c < 18t$). We can thus conclude that, under reasonable assumptions, consumer surplus is higher in the full adoption scenario, and lower for the no adoption scenario.

Proposition 4: Under partial-adoption, the restaurants that adopts the platform will increase their prices relative to the non-adopting restaurant.

Proposition 5: Under partial-adoption, restaurants that participate in OT will enjoy greater profits than non-participating restaurants.

The four scenarios considered configure a prisoner's dilemma. Comparing the outcomes in the four scenarios shows that the best response for each restaurant to whatever decision the other restaurant takes is to adopt the platform. Thus, the pure strategy Nash equilibrium is for both restaurants to adopt. Even though adoption will not increase the profits of restaurants if they both adopt, the best strategy is for them to adopt in order to prevent losing customers to the other restaurant.

Proposition 6: Adoption of OT by a restaurant creates incentives for the competing restaurant to adopt OT.

OpenTable adoption in NYC is more nuanced than our simplified model. However, the model provides a framework for understanding how restaurants will react if a close competitor joins the platform, and to determine how the benefits and costs of the platform will be distributed between restaurants and diners. Evidently, not all restaurant will adopt at the same time. Thus, the partial adoption scenario gives some indications on what happens in the transient period when only some restaurants have joined the platform. Under partial adoption, adopters will steal business from non-adopters, and will be able to command a higher price by offering additional value. Early-adopters will be able to profit from the platform until the rest of the restaurants join. Once that happens, market shares revert to pre-adoption levels and restaurants will make no additional profits by participating in the platform. However, they will be locked into the platform, as if they leave, they would lose customers to restaurants that remain in the platform.

4 Data Description and Empirical Strategy

To test the propositions of our model, we need information on active restaurants in NYC, of OpenTable participation in NYC, and restaurants' prices. Ideally, we also need restaurants' profits, which are not easily obtained. We study survival as a proxy for restaurants' profits, assuming that establishments with negative profits exit. We rely on three sources to get the information: the NYC DOHMH restaurants' inspection database; historical captures of OpenTable's website stored in the Internet Wayback Machine; and data compiled from the Zagat survey.

The NYC DOHMH is required to inspect all new restaurants in the city before they open, and to conduct yearly sanitary inspections of all existing restaurants. Some restaurants are inspected more than once a year if they committed a violation that requires them to make repairs, if they had too many health code violations, or if they request to be re-inspected to improve their preliminary grade. Information on these inspections is available to the public, and since 2011, restaurants are assigned a letter grade according to the results of their inspection and are required to post that grade in a prominent place visible from outside the restaurant. We use inspections' data to get a census of active restaurants in NYC over time. Through a Freedom of Information Act request to NYC's DOHMH, we obtained results of all inspections conducted between July 1, 2007 through September 30, 2016. We complement this data with information obtained from NYC's Open Data website (which contains information on recent inspections) to obtain all inspection through July 2017.

To obtain a list of all restaurants that have participated in OpenTable over time, we rely on the Internet Wayback Machine (IWM). The IWM is an online archive that scrapes major websites periodically and saves their content for future reference. Using this website, we obtained a list of all restaurants that participated in OT since 2002. Overall, we put together information on OT participation between February 2002 and November 2014. Finally, we use the Zagat survey to obtain information on restaurant prices. Zagat is a restaurant guide started in 1979 by Tim and Nina Zagat. It consists of a survey that is conducted over the course of a year and asks respondents to rate their dining experience at restaurants they visit. Each survey is composed by responses of about 45,000 surveyors that eat out ~3 times per week[6]. Unlike other restaurant guides and directories, Zagat reports the average cost of dining (defined as a main course and a drink) rather than a price range. For NYC, the guide includes information for about 2,000 restaurants per year. To obtain restaurant prices over time we scanned NYC Zagat guides published between years 2005 and 2016, and using optical character recognition (OCR) software created a dataset that contains: Restaurant name, address, cuisine, Zagat scores (for food, décor, and service), and price. The values extracted by the OCR software were manually

[6] Until 2014, each Zagat guide contains a page with details about the survey. For example, the 2014 guide reports 48,114 surveyors that allegedly eat 4.9 meals out per week (Zagat 2014, pp.5).

checked to ensure accuracy.[7] Between consecutive Zagat guides there is an attrition rate of about 20%. Some of this restaurant exit (about a third), while the rest are no longer included in the guide and are replaced for new places (or newly covered places). The attrition rate remains roughly constant over time.

A difficulty for our empirical analysis is that the decision to join OpenTable is endogenous and likely correlated with our dependent variables of interest. It is reasonable to expect that high quality restaurants should be more likely to adopt an innovation that enhances diners' experience, and at the same time those places should be more likely to command higher prices and have better survival chances. We take advantage of the 12 years of panel data we compiled on restaurant prices and OT adoption to implement a difference-in-difference analysis. In our estimations, we use regressions of the form:

$$X_{t+1} = R_i + B_t + g * Z_{it} + \sigma * OT_{it} + e_{it}$$

In this regression, R_i is a vector of restaurant fixed effects, and B_t is a vector of time fixed effects. Z_{it} is a vector of restaurant's *i* characteristics at time *t*, which are obtained from the Zagat guide and include the average price of meal, and ratings for: Food, décor, and service. OT_{it} is a dummy equal if restaurant *i* participated in OT during period *t*, and zero otherwise. Finally, e_{it} is the error term. In all estimations, we use robust standard errors clustered at the restaurant level. In this context, σ corresponds to the difference-in-difference estimator of OpenTable's effect on restaurants' price *X*. Using restaurant fixed effects controls for time-invariant characteristics of restaurants that may make them more likely to adopt OT. This approach does not fully eliminate the endogeneity concerns relating to self-selection into OpenTable adoption. Specifically, it cannot account for time-varying variables that simultaneously influence restaurants' likelihood of adopting OT, and restaurants' prices. Although it would be ideal to find a source of exogenous variation of OT adoption, or a valid instrument for OT adoption, this doesn't seem feasible in our setting. Thus, to account for self-selection, we use a Heckman-style endogenous treatment effect model. As exclusion condition, we use the rate of OT adoption by neighboring restaurants that serve food in a different cuisine. In the Zagat guide, restaurants are categorized in over 100 types of cuisines. We map this classification into 13 broadly defined food categories that group restaurants that are likely to compete[8]. We expect adoption by restaurants that are located nearby, but that do not directly compete in the same type of cuisine to influence adoption by increasing awareness about the platform, but not to influence demand and prices. To further test the robustness of our results, we perform an additional test where we relate the fraction of guests that use OT to make their reservations with price increases. The logic behind this strategy is that while adoption of OT is endogenous, the reliance of guests

[7] OCR software commonly mistakes numbers when the font used is not optimized for character recognition. For example, 3s and 8s, or 1s and 7s, are commonly mistaken for each other.

[8] The categories include: American, Italian, French, Japanese, Mexican, Asian, Latin American, European, Bakery/Cafes, Pubs/Bars, African/Australian, Middle Eastern, and Others.

on OT to make reservation does not depend on the restaurant and is thus less affected by endogeneity concerns. To obtain a proxy for the fraction of guests that use OT we collect information on the number of reviews received by restaurants in OT and on Yelp (a popular restaurant review platform).

5 Empirical Analysis

Adoption

In Figure 2, we show the fraction of restaurants listed in Zagat that participate in OT[9] over time. We divide restaurants in terms of price quartiles with respect to all restaurant listed in the same year. Restaurants prices in the top 25% in 2014 ranged between $54 and $585 dollars. Restaurant prices in the 25% to 75% group ranged between $29 and $53. Prices in the bottom 25% ranged between $6 and $28. OpenTable reaches a remarkable adoption rate in year 2011, with ~70% of top priced restaurants participating in the platform, and ~50% of mid-priced restaurants. From 2011 the adoption rate remains mostly constant. Adoption by restaurants with prices in the lower quartile remains rare throughout the period studied, which is to be expected as they probably won't benefit from the platform (as they possibly don't offer reservations, or their per guest margin is too low to justify OT's fee). By 2014 adoption by diners was also high, with 56% of Zagat surveyors stating that they typically make reservations online (Zagat 2014, pp. 5).

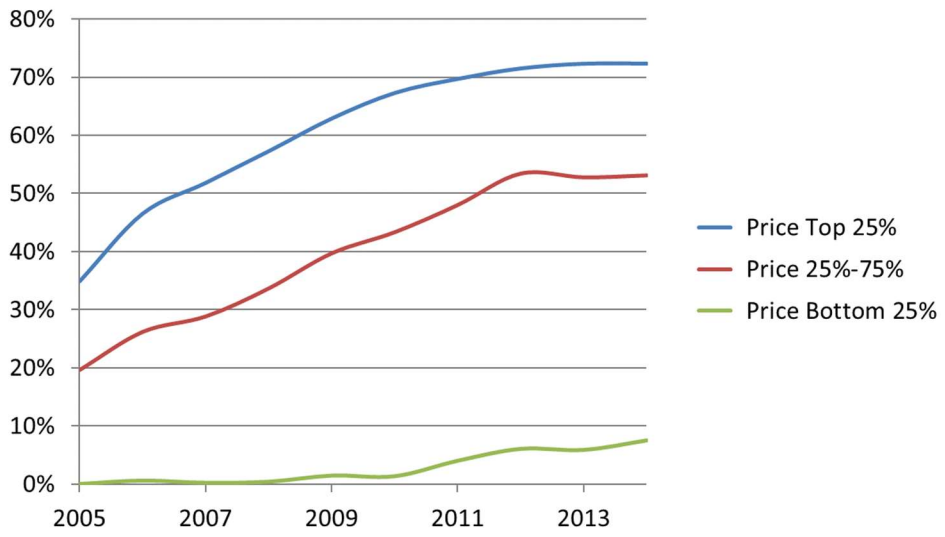

Figure 2: Fraction of Restaurants Listed in Zagat that Participate in OT over Time, by Price Quartiles.

[9] We say that a Restaurant participated in OT during year y if the restaurant was listed in at least half of all the screenshots that the IWBM took of OT's website in year y. The last capture we were able to obtain from the IWBM is from November 2014. Thus, for 2015 we assume that OT participation remained as in 2014.

One of the platform's features that can be inferred from proposition 6 of our model is that adoption by close competitors will create incentives for restaurants to join. If this is the case, increasing adoption over time should not make any restaurant more likely to join, but instead, make adoption by close competitors of adopters more likely. Figure 3 shows all restaurants that are listed in Zagat and participate in OT in 2005, 2008, 2011, and 2014. In each panel, blue dots represent restaurants that did not participate in the previous period.

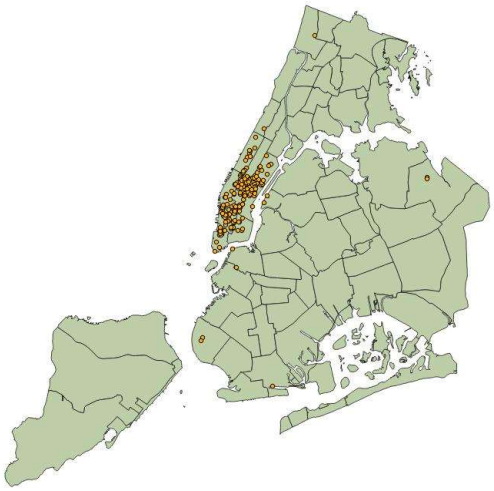

Figure 3.1: Restaurants listed in Zagat that Participated in OT in 2005

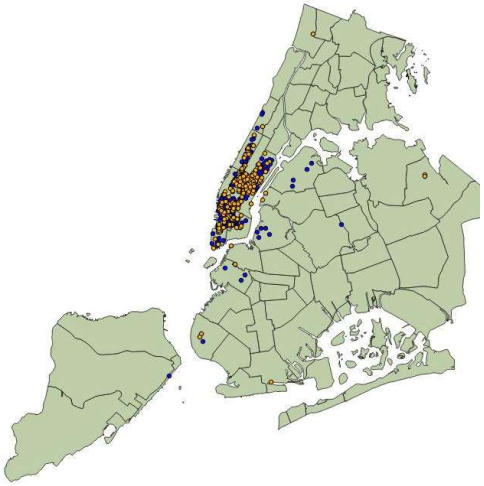

Figure 3.2: Restaurants listed in Zagat that Participated in OT in 2008

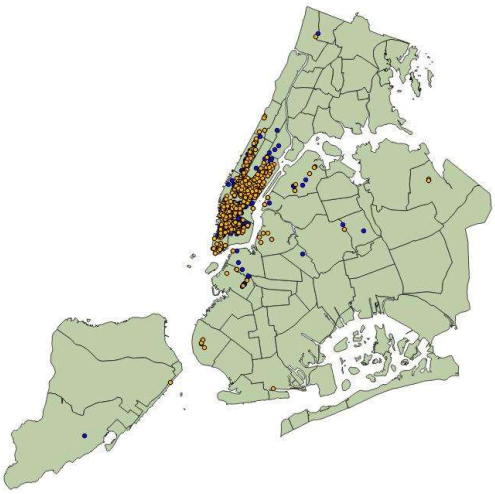

Figure 3.3: Restaurants Listed in Zagat that Participated in OT in 2011

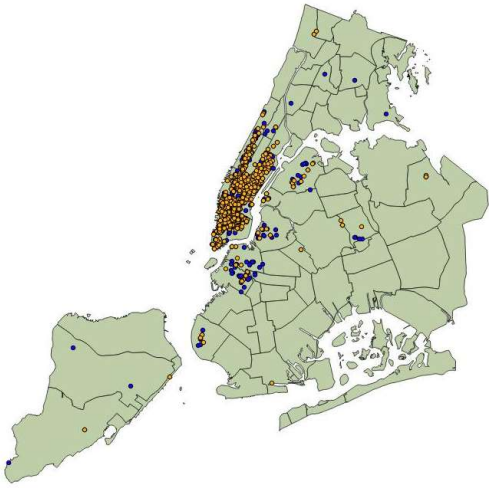

Figure 3.4: Restaurants Listed in Zagat that Participated in OT in 2014

Table 2: Adoption Models A1-A3

	A1	A2	A3	A4	A5
OT (t-1)	3.491***	3.442***	3.445***	3.444***	3.443***
	(0.0594)	(0.0592)	(0.0590)	(0.0591)	(0.0589)
Price	0.00877**	0.00865**	0.00841**	0.00842**	0.00848**
	(0.00393)	(0.00388)	(0.00384)	(0.00385)	(0.00378)
Food	0.00994	0.00549	0.00570	0.00563	0.00533
	(0.00627)	(0.00640)	(0.00634)	(0.00635)	(0.00626)
Time Trend		0.0332***	0.0104	0.0174	0.0149
		(0.00478)	(0.00651)	(0.0112)	(0.0110)
Q. Mile Adoption Rate			0.624***	0.659***	
			(0.129)	(0.135)	
1 Mile Adoption Rate				-0.226	
				(0.289)	
Q. Mile Adoption Rate Same Cuisine					0.221***
					(0.0712)
Q. Mile Adoption Rate Different Cuisine					0.365***
					(0.133)
1 Mile Adoption Rate Same Cuisine					0.320**
					(0.131)
1 Mile Adoption Rate Different Cuisine					-0.400
					(0.261)
Neighborhood F.E.	Yes	Yes	Yes	Yes	Yes
Cuisine F.E.	Yes	Yes	Yes	Yes	Yes
Constant	-3.266***	-3.405***	-3.230***	-3.262***	-3.080***
	(0.418)	(0.418)	(0.414)	(0.414)	(0.417)
Observations	21,386	21,386	21,386	21,386	21,386

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To determine if adoption by neighboring restaurants influences adoption in a framework that allows to control for covariates, and to test different models that could be used in the selection equation of the endogenous treatment effect models we use later, we estimate a series Probit models (Table 2). In these models, the dependent variable is a dummy equal to 1 if restaurant *i* participates in OT in time *t,* and zero otherwise. In Model A1, we only include controls for restaurant characteristics, neighborhood fixed effects, and cuisine fixed effects. The neighborhood fixed effects are defined according to the "community district" the restaurant is located in.[10] They seek to control for neighborhood characteristics that may make adoption more likely for restaurants located there, such as, for example, the concentration of restaurants in the area. The restaurant characteristics covariates include: participation in OT in time *t-1*, as restaurants that have joined the platform are likely to remain in the platform; restaurant price; and food score. We don't include scores for décor and service as they are highly correlated with price. The coefficient for price is positive and significant, which is consistent with the patterns shown in Figure 2. The coefficient for food is not significant. As adoption is increasing in time, in model A2 we add a time trend variable. The coefficient is positive and significant, which

[10] There are 59 community districts in NYC (12 in Mahattan, 12 in the Bronx, 8 in Brooklyn, 14 in Queens, and 3 in Staten Island).

is consistent with increasing adoption over time. In model A3, we add a variable that accounts for the fraction of restaurants listed in Zagat within 0.25 miles of restaurant *i* that participate in OT (Quarter Mile Adoption Rate). In line with proposition 6, the coefficient estimate is positive and significant. Moreover, after introducing this variable, the effect of the time trend greatly diminishes and becomes insignificant. This provides added support for proposition 6, as it indicates that adoption is not simply increasing on time. Instead, restaurants that join at later periods are those located nearby restaurants that had already joined. To further test whether the quarter mile adoption rate variable is accounting for adoption within neighboring restaurants, and not just overall growth of OT in the city, in model A4 we add an additional variable that accounts for the fraction of restaurants within a one-mile radius of restaurant *i* that participate in OT (One Mile Adoption Rate). The coefficient for this variable is close to zero and not significant.

In model A5 we explore the influence of adoption by restaurants in the same or in different cuisines. As explained in section 4, we classified restaurants in 13 broad cuisine types that aggregate restaurants likely to directly compete. OpenTable Adoption by restaurants in the same cuisine should influence adoption by competitors in the way outlined in our model. We posit that adoption by restaurants in a different cuisine type influences adoption by increasing awareness about the platform. As this awareness corresponds to vicarious information, we expect its effect to be geographically bounded to neighboring restaurants, which are more likely to know of the actions of one another. The coefficient estimates we obtain are consistent with this explanation. The coefficient for OT adoption rate at restaurants in a different cuisine is positive and significant when considering restaurants in a quarter mile radius, and not significant when considering restaurants in a one-mile radius. In contrast, the coefficient for OT adoption rate at restaurants in the same cuisine is positive and significant at both a quarter mile and a one-mile radius. In non-reported results, available from the authors on request, we tested a series of alternative specifications including: Using time fixed effects instead of a time trend variable, using a linear probability model with restaurant fixed effects, using a Probit model with restaurant fixed effects (including only restaurants that adopt OT at some point in our database), and excluding lagged OT adoption from the control variables. In all alternative specifications, results are qualitatively equivalent.

Price

To study the effect of OT on price, we analyze price differences over periods of two years. We used two years, instead of one, because we observe that in many cases prices (and ratings) reported in Zagat are not updated in every edition of the guide[11]. Table 3 presents four models based on the difference-in-difference framework explained in section 4. Model M1 only includes restaurant characteristics covariates, firm fixed effects, and the OT participation dummy. The coefficient of the OT dummy corresponds to the difference-in-difference

[11] We also perform the analysis using yearly price differences. Results are analogous, although in some models we encountered convergence issues.

estimator, and it is positive and marginally significant. The coefficient indicates that OT participation is related with a price premium of $0.33.

Table 3: Price Models P1-P3

	M1	M2	M3
OT	0.330*		-0.0731
	(0.199)		(0.249)
OT x Before 2011		-0.232	
		(0.270)	
OT x From 2011		0.745***	
		(0.198)	
High Adoption One Mile Same Cuisine			-0.0696
			(0.169)
OT x High Adoption One Mile Same Cuisine			1.156***
			(0.329)
Price	0.387***	0.382***	0.382***
	(0.120)	(0.119)	(0.119)
Price Sq.	0.000165	0.000169	0.000169
	(0.000104)	(0.000103)	(0.000103)
Service	-0.0253	-0.0267	-0.0265
	(0.0294)	(0.0295)	(0.0292)
Food	0.0131	0.0143	0.0127
	(0.0159)	(0.0159)	(0.0160)
Décor	0.0193	0.0247	0.0210
	(0.0236)	(0.0231)	(0.0234)
Constant	23.54***	23.71***	23.77***
	(3.704)	(3.688)	(3.666)
Restaurant Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	15,056	15,056	15,056
R-squared	0.984	0.984	0.984

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A key motivation of our study is to determine how the effect of the platform changes as adoption grows. According to our theoretical model, the effect of adoption on prices depends on the fraction of users that are aware of the platform. In models M2 and M3 we examine how the OT coefficient changes as the platform's popularity increases in two different ways. We first take advantage of increasing adoption over time. As shown in Figure 2, OT adoption peaks around 2011 and remains stable thereafter. Thus, in model M2 we estimate the OT coefficient separately for observations up to 2011, which represents the effect of OT on prices in the growth period of the platform, and for observations after 2011, which capture the effect of the platform on prices once its adoption rate is high and stable. The coefficient estimates for OT before 2011 is not significant, while the OT coefficient after 2011 is positive and significant. It implies OT adoption is associated with a price increase of U$0.75 once its adoption rate was high and stable. We next test how the OT effect on

prices changes with increasing adoption at competing restaurants. In model M3 we define a dummy variable that is equal to 1 if over half of the restaurants located in a one-mile radius of restaurant *i*, and that serve food in the same cuisine, participate in OT and zero otherwise (High Adoption One Mile Same Cuisine)[12]. We introduce this variable by itself and interacted with OT. The coefficient estimate of the interaction is positive and significant, and it is higher than the OT coefficient obtained in model M2.

Table 4: Price Models M4-M6

	M4		M5		M6	
VARIABLES	Price	OT	Price	OT	Price	OT
OT	0.388**		-0.296		-0.111	
	(0.184)		(0.247)		(0.212)	
OT x After 2011			0.992***			
			(0.181)			
Not OT x High Adoption 1 M Same Cuisine					-0.0713	
					(0.126)	
OT x High Adoption 1 M Same Cuisine					1.093***	
					(0.194)	
Lagged Price	0.387***	0.00265***	0.382***	0.00266***	0.382***	0.00266***
	(0.0733)	(0.000862)	(0.0734)	(0.000864)	(0.0733)	(0.000863)
Lagged Price Sq.	0.000165		0.000169		0.000169	
	(0.000103)		(0.000103)		(0.000103)	
Service	-0.0253	0.0164**	-0.0267	0.0164**	-0.0264	0.0164**
	(0.0177)	(0.00822)	(0.0177)	(0.00823)	(0.0174)	(0.00823)
Food	0.0133	-0.0224***	0.0141	-0.0223***	0.0126	-0.0224***
	(0.0129)	(0.00685)	(0.0129)	(0.00687)	(0.0130)	(0.00686)
Décor	0.0185	0.0648***	0.0255	0.0648***	0.0215	0.0648***
	(0.0202)	(0.00772)	(0.0200)	(0.00771)	(0.0201)	(0.00771)
OT (t-1)		3.631***		3.630***		3.631***
		(0.0549)		(0.0548)		(0.0548)
Q. Mile OT Adoption Rate Different Cuisine		0.669***		0.668***		0.668***
		(0.109)		(0.109)		(0.110)
Time Trend		-0.0244***		-0.0243***		-0.0243***
		(0.00742)		(0.00743)		(0.00743)
Time Period Fixed Effects	Yes		Yes		Yes	
Restaurant Fixed Effects	Yes		Yes		Yes	
athrho	-0.0188	(0.0289)	0.0181	(0.0336)	0.0114	(0.0329)
lnsigma	1.173***	(0.0477)	1.172***	(0.0477)	1.171***	(0.0477)
Constant	12.93***	-2.741***	12.89***	-2.742***	13.01***	-2.742***
	(1.413)	(0.155)	(1.410)	(0.156)	(1.418)	(0.156)
Observations	15,056	15,056	15,056	15,056	15,056	15,056

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To further evaluate the robustness of our results, we repeat the analysis using an endogenous treatment effects regression model to account for self-selection bias. We specify the selection equation based in model

[12] In non-reported results, available from the authors on request, we repeat this model using continuous adoption rates instead of a dummy variable. The results are equivalent. We present this functional form to simplify the interpretation of the results.

A3, but instead of using the overall OT adoption rate in a quarter mile radius, we consider only OT adoption at restaurants in different cuisines. We do this to reduce the likelihood that the adoption rate variable we use in the adoption equation is correlated with price. Results are reported in Table 4. Model M4 is the equivalent of model M1, model M5 is analogous to model M3, and model M6 to model M3. The magnitudes of the OT coefficients are similar to the coefficients we obtained in the OLS models. The endogenous treatment effect model suggests that the OLS estimates are biased, but the magnitude of the bias is negligible. However, we cannot reject the null hypotheses of no correlation between the OT adoption errors and the price errors. This implies that the OLS model may be more appropriate. Overall, our estimations provide support for propositions 1 and 2. OT appears to be associated with an increase in price, and this increase is steeper later in the sample, when OT adoption is higher, and for restaurants in cuisines and locations with high OT adoption.

Price Robustness Test

Proposition 2 states that the driving force behind price increases at restaurants that adopt OT is the fraction of patrons that choose to make reservations using the platform. Intuitively, if a restaurant must pay OT $1 for every diner, the seemingly small fee adds up to a significant amount that pushes the restaurant to raise prices to recover lost revenue. In models M2 and M3 we used time and adoption at competing restaurants as proxies for OT prevalence. We now use a more direct measure of the fraction of diners that use OT. Specifically, we include an additional variable with the ratio between the number of reviews for the restaurant posted in OT's website over the number of reviews for the restaurant posted in Yelp (a popular online review platform). Besides providing a more exacting way for testing proposition 2, this also helps alleviate some of the endogeneity concerns. While a restaurant's decision to adopt OT is endogenous, the establishment has little control over how diners choose to make reservations. Additionally, we can use the number of reviews posted in Yelp as a proxy for demand and use it to rule out the alternative explanation that the price increase we observe is due to an increase in demand, rather than being driven by participation in OT.

To implement this test, we collect additional data. We attempt to collect all reviews posted in OT and Yelp for all restaurant in our dataset. However, we are not able to find information for all restaurant due to different reasons. In the case of OT, we can get all reviews for restaurants that are still active and currently participating in the platform, and all reviews for a limited number of restaurants that no longer exist, or that are still active but no longer participate in OT. We obtain all reviews for about a third of the restaurants that use OT at any point in time in our sample. To complement this data, we extract from the Internet Wayback Machine the number of reviews reported in the archived copies of OT's restaurant directory by city. The number of recent reviews a restaurant has received is reported in these listings from 2010. We use this data, along with the actual reviews we collected, to estimate the number of reviews received per restaurant per year since 2010. Overall, we obtain approximated yearly review counts for 77% of restaurants in our sample that participate in OT at any time, and for all restaurants since 2010. In the case of Yelp, we are able to get

information for most restaurants, as Yelp keeps reviews for restaurants that have exited. Overall, we extracted reviews from Yelp for 90% of the restaurants in our sample. The restaurants we were not able to find in Yelp are in most cases establishments that closed in the early years of the sample.

An additional challenge we face for this test is that the popularity of review platforms considerably increased during the time of our study. Reviews are rare early on, and the popularity of Yelp and OT fluctuates throughout the sample. In the first years, there are many reviews posted in OT, but only a few in Yelp. Towards the end of the sample, there are many reviews posted in both platforms. This is most likely due to OT entering much earlier than Yelp (1998 vs 2004). To account for this, we normalize the number of reviews received by restaurant *i* in platform *p* during year *y*, by the average number of reviews received by all restaurants in our sample in platform *p* during year *y*. We then define the ration of OT/Yelp reviews as:

$$Ratio\ OT/Yelp_{iy} = \frac{1 + Normalized\ \#\ of\ OT\ Reviews\ for\ Restaurant\ i\ in\ year\ y}{1 + Normalized\ \#\ of\ Yelp\ Reviews\ for\ Restaurant\ i\ in\ year\ y}$$

We add 1 to both the numerator and the denominator to prevent the ratio from becoming undefined if restaurant *i* did not receive any reviews in Yelp. We exclude from the analysis all restaurants that we couldn't get OT reviews (and that participated in OT at any time), and all restaurants that we could not locate in Yelp.

Table 5: Price Models P7-P10

	M7	M8	M9	M10
OT	0.732**	0.590*	0.278	0.0501
	(0.370)	(0.356)	(0.346)	(0.370)
Ratio OT/Yelp		1.300***		1.001***
		(0.412)		(0.358)
# Yelp Reviews		0.167		0.299**
		(0.134)		(0.139)
Price	0.167	0.169	0.485**	0.483**
	(0.134)	(0.135)	(0.233)	(0.231)
Price Sq.	0.00007	0.00007	0.00004	0.00004
	(0.000310)	(0.000311)	(0.000230)	(0.000228)
Service	-0.0137	-0.0105	-0.0641	-0.0668
	(0.0221)	(0.0217)	(0.0525)	(0.0516)
Food	0.00120	-0.000484	-0.0128	-0.0135
	(0.0151)	(0.0152)	(0.0176)	(0.0182)
Décor	-0.00146	0.00387	-0.0347	-0.0274
	(0.0317)	(0.0328)	(0.0320)	(0.0331)
Constant	36.88***	35.53***	19.84***	19.04***
	(5.343)	(5.476)	(6.725)	(6.809)
Year Fixed Effects	Yes	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,660	8,660	6,954	6,954
R-squared	0.985	0.986	0.987	0.987

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In model M7 in table 5, we replicate model M1 using the subsample of restaurants for which we can obtain OT (approximated) and Yelp (actual) reviews. Note that this subsample drops all observations before 2010, which explains why the OT coefficient we obtain is close to the "OT x From 2011" coefficient in model

M3. In model M8 we introduce the Ratio OT/Yelp and the normalized number of Yelp reviews variables. The coefficient of the Ratio OT/Yelp is positive and significant at the 1% level. Moreover, the magnitude of the OT dummy coefficient diminishes and is now only marginally significant. To check the consistency of our estimated number of OT reviews, in model M9 and M10 we repeat the analysis but using only the restaurants that participate in OT for which we could obtain actual reviews (instead of the yearly estimated reviews). In model M9, the OT dummy is not significant, which is hardly surprising, as we drop 2/3 of restaurants that ever participate in the platform. In model M10 we obtain results equivalent to model M8, which help us rule out that the result we obtained is an artifact of the way we estimated the yearly number of reviews posted in OT.

Survival

To analyze survival, we face the additional challenge of matching observations to the DOHMH inspections database. This is a cumbersome process, as in many cases restaurant names are recorded with different variations in Zagat, OpenTable and the DOHMH inspections dataset. Moreover, it is also frequent that restaurants have multiple locations under the same name. To match restaurants across databases, we use an algorithm that compares geographical coordinates extracted from addresses[13] to identify potential matches, and then selects the correct match by comparing names. For each restaurant in the dataset we find all restaurants in the DOHMH dataset that are located within a radius of 0.05 miles. Within this list of potential matches, we use a string comparison algorithm and eliminate all potential matches that score below certain threshold.[14] If one of the potential matches is a perfect name match, we consider the observation as matched and discard other potential matches. If there is only one potential match, we also consider the observation as matched. For cases with multiple potential matches and no perfect match, we manually inspect the alternatives and select the correct match (or discard the observation). Restaurants that are not matched are not considered in the analysis. Overall, we were able to match 71% of restaurants listed in Zagat to the DOHMH database. As we have information on inspections between July 2007 and July 2017, we include in our analysis restaurants that were listed in Zagat between 2008 and 2015 and were inspected by the DOHMH at least once during (or after) the year they were first listed in Zagat. For our survival analysis, we consider that a restaurant exits in year Y if it was not inspected in year Y+1 (or any year thereafter). Restaurants that were last inspected on 2016 or after are considered right censored.

[13] To find the geographical coordinates of addresses we used Google's geo-location API.
[14] We use the Jaro-Winkler string comparison algorithm and set a minimum score of 0.7 as the threshold to be considered a potential match.

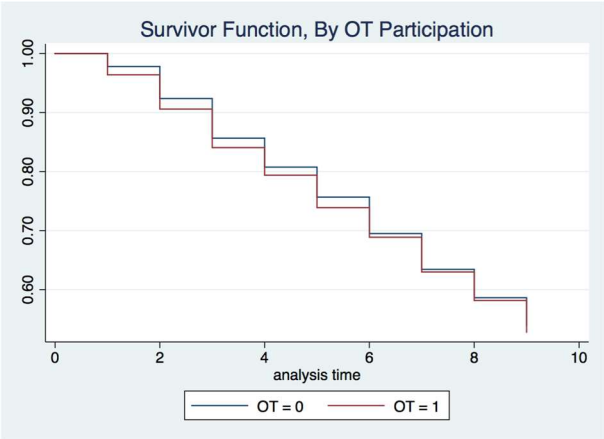

Figure 4.1: Survivor Function by OT Participation

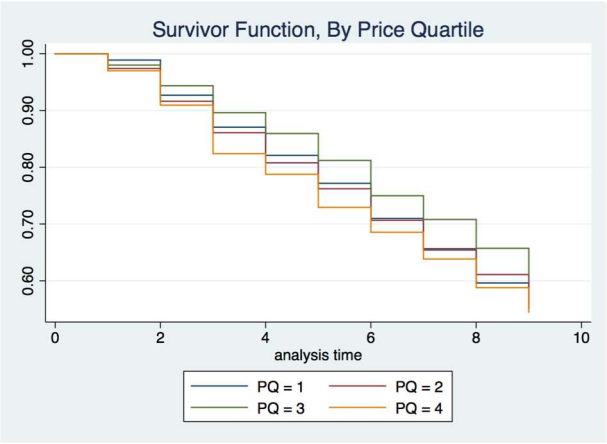

Figure 4.2: Survivor Function by Price Quartile

We seek to determine whether participating in OT has a positive effect on increasing a restaurant's likelihood of survival. As before, OT adoption is dependent on other covariates that are also likely to influence survival. To get a sense of how different variables influence survival, Figure 4 shows the Kaplan-Meier survival curves for restaurants by OT participation, and by price quartile (the analysis time starts from 2008). Figure 4.1 shows that restaurants that participate in OT actually exit at a higher rate than restaurants that do not participate in OT. Figure 4.2 suggests this may be driven by the fact that the most expensive restaurants (price quartile 4) have lower survival rates than other restaurants and, as we showed in figure 2, these restaurants are also more likely to participate in OT. These patterns reveal a complex relationship between price, OT adoption, and survival. To untangle this relationship, we use Cox-proportional hazard models. To estimate these models, we take advantage of the equivalence between a Cox-proportional hazard model and a Poisson model where each spell has been divided into *n* pseudo observations representing each of the periods the subject was at risk (Holford, 1980; Laird and Oliver, 1981). Using this equivalence allows us to test the robustness of our result to endogeneity concerns by repeating the analysis using Poisson regressions with endogenous treatment effects. This is particularly relevant in this analysis, as we cannot use the difference-in-difference framework we used for the price analysis because restaurant fixed effects are not identified in this setting.

A difficulty in implementing a Cox proportional hazard model with our data is that not all surviving restaurants are continuously listed in Zagat. Some restaurants stop being covered to make room for new places. For the establishments that are no longer included in the guide, we don't have updated information on prices and ratings. We use two approaches to address this problem. The first approach (shown in the regressions) consists in including in the analysis only restaurants that are continuously covered in Zagat until they exit, or up to the last year of our survival analysis. The second approach (not reported, but available from the authors on request) consisted in inputting the missing information for restaurants that are no longer listed from the last data point we had, and adding a dummy variable equal to one if the restaurant was not listed in Zagat in the

year of analysis to control for unobservables that may have led to Zagat's decision not to cover that restaurant anymore. The coefficient estimates obtained with both approaches are similar.

Table 6: Cox-Proportional Hazard Models S1-S4

	S1	S2	S3	S4
OT	-0.0585		0.0556	0.127
	(0.121)		(0.139)	(0.143)
OT x Before 2011		-0.0175		
		(0.166)		
OT x From 2011		-0.0877		
		(0.147)		
High Adoption 1M Same Cuisine			-0.0144	
			(0.169)	
OT x High Adoption 1M Same Cuisine			-0.303	
			(0.217)	
High Adoption QM Same Cuisine				0.149
				(0.129)
OT x High Adoption QM Same Cuisine				-0.456**
				(0.201)
P0	-0.00249	-0.00247	-0.00273	-0.00231
	(0.00672)	(0.00672)	(0.00675)	(0.00672)
P0sq	6.22e-06	6.33e-06	8.22e-06	7.33e-06
	(2.17e-05)	(2.17e-05)	(2.17e-05)	(2.17e-05)
S0	0.00728	0.00726	0.00667	0.00611
	(0.0124)	(0.0124)	(0.0122)	(0.0120)
F0	-0.0845***	-0.0849***	-0.0848***	-0.0847***
	(0.0105)	(0.0106)	(0.0105)	(0.0106)
D0	-0.0177	-0.0179	-0.0196	-0.0193
	(0.0164)	(0.0165)	(0.0165)	(0.0164)
Neighborhood F.E	Yes	Yes	Yes	Yes
Cuisines F.E.	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
Constant	-2.456***	-2.455***	-2.448**	-2.533***
	(0.942)	(0.943)	(0.951)	(0.932)
Observations	6,905	6,905	6,905	6,905

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the 8 years of analysis, a total of 3,627 restaurants were listed in Zagat and inspected by NYC's DOHMH. Based on the date of the last inspection, we can infer that 1,315 (36%) of those restaurants exit at some point over the analysis period. In the first model shown in table 7 (S1) we only introduce the OT dummy variable, which in these models is equal to 1 if the restaurant was participating in OT in the year of analysis and zero otherwise, along with controls for price, ratings (food, décor, and service), and fixed effects for year, neighborhood, and cuisine. The only coefficient estimate that is statistically significant is that associated with food rating. It implies that an additional point if food rating is associated with a 3% decrease in failure probability. The coefficient corresponding to OT participation is not statistically significant. In our analytical model, OT participation is not expected to have any effect on profits in equilibrium (i.e. under full adoption). However, proposition 5 of the model suggests that if a restaurant does not participate in OT once the platform

has been adopted by competing restaurants and is popular among diners, its profits would be negatively affected as it loses customers to competing restaurants that participate in the platform. To test this notion, similarly to what we did in the price analysis, in models S2 and S3 we examine if the effect of OT on survival changes after 2011 (S2), and after it has been adopted by more than half of restaurants in the same cuisine within a one-mile radius (S3). We don't find a significant effect in either of these models. In model S4 we repeat model S3 but using the fraction of restaurants in the same cuisine within a quarter mile radius. In this model, the coefficient of the interaction of the OT dummy with the high adoption dummy is statistically significant. To interpret the coefficient, we compute the average treatment effect, which suggests OT participation for restaurants for whom at least 50% of restaurants in the same cuisine within a quarter mile radius participate in OT is associated with a 2.2% reduction in failure probability. This effect is only statistically significant at the 10% level.

A problem with the Cox-proportional hazard models presented above is that the baseline hazard rate of failure may differ across restaurants due to unobservable characteristics. Moreover, these unobservables may be correlated with the decision to self-select into OT participation and further confound the results. Unfortunately, we cannot control for these unobservable characteristics using restaurant fixed effects, as they cannot be identified in survival models. Thus, we repeat the analysis presented above using Poisson regressions with endogenous treatment effects. We use the same exclusion condition as in the price models presented earlier, i.e. the OT adoption rate by restaurants in a quarter mile radius in a different cuisine. Results are presented in table 8. Model S5 is analogous to model S2. The coefficients associated with OT participation are not statistically significant. In model S6 we replicate model S3. In this case, the coefficient of the interaction between OT and high OT adoption by restaurants in the same cuisine in a one-mile radius is marginally significant. The average treatment effect of OT participation implies a 1% reduction in the probability of failure for these restaurants, although the effect is not statistically significant. In model S7, which is analogous to model S4, we obtain a similar result. While the coefficient of the interaction term is statistically significant, the average treatment effect of participating in OT for restaurants in high adoption cuisines and locations is not. Note that, contrary with what happened in our price analysis, in all these models we can reject the null hypotheses that the error terms of the selection and the outcome equations are uncorrelated, confirming the need of endogenous treatment effect models. Overall, we don't find evidence of a significant relationship between OT adoption and an increase in the probability of survival.

Table 7: Poisson Regression With Endogenous Treatment Effects S5-S7

	S5		S6		S7	
VARIABLES	dead	OT	dead	OT	dead	OT
OT	0.0590		0.134		0.204	
	(0.172)		(0.147)		(0.150)	
OT x From 2011	-0.0717					
	(0.199)					
Not OT x Top Adoption 1M SC			-0.00967			
			(0.182)			
OT x Top Adoption 1M SC			-0.313*			
			(0.188)			
Not OT x Top Adoption QM SC					0.143	
					(0.134)	
OT x Top Adoption QM SC					-0.455**	
					(0.203)	
Price	-0.000301	0.00836***	-0.000627	0.00836***	-0.000238	0.00836***
	(0.00699)	(0.00239)	(0.00701)	(0.00239)	(0.00696)	(0.00239)
Price Sq.	7.76e-07		2.84e-06		2.04e-06	
	(1.94e-05)		(1.92e-05)		(1.95e-05)	
Service	0.00120	0.00561	0.000731	0.00562	0.000227	0.00561
	(0.0133)	(0.0111)	(0.0131)	(0.0111)	(0.0129)	(0.0111)
Food	-0.0831***	-0.0395***	-0.0830***	-0.0395***	-0.0829***	-0.0395***
	(0.0109)	(0.00796)	(0.0109)	(0.00797)	(0.0109)	(0.00796)
Décor	-0.0250	0.0965***	-0.0268	0.0965***	-0.0265	0.0965***
	(0.0175)	(0.0110)	(0.0175)	(0.0110)	(0.0173)	(0.0110)
OT (t-1)		3.744***		3.744***		3.744***
		(0.0967)		(0.0968)		(0.0968)
QM Adoption Rate DC		0.411**		0.411**		0.411**
		(0.188)		(0.188)		(0.188)
Time Trend		-0.0214*		-0.0214*		-0.0214*
		(0.0129)		(0.0129)		(0.0129)
Neighborhood F.E.	Yes		Yes		Yes	
Cuisine F.E.	Yes		Yes		Yes	
Time F.E.	Yes		Yes		Yes	
athrho	-1.612***	(0.0756)	-1.618***	(0.0733)	-1.618***	(0.0733)
lnsigma	-1.873***	(0.436)	-1.834***	(0.411)	-1.836***	(0.411)
Constant	-2.343**	-2.866***	-2.336**	-2.866***	-2.417**	-2.866***
	(1.062)	(0.219)	(1.065)	(0.219)	(1.062)	(0.219)
Observations	6,431	6,431	6,431	6,431	6,431	6,431

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Survival Robustness Test

As in the price analysis, by using information on the number of reviews a restaurant gets on OT and on Yelp, we can directly test how the effect of OT on survival changes as the use of the platform by diners increases. According to proposition 3, the fraction of diners that use OT to make their reservations should not have a significant effect on profits (and thus on survival). In theory, as the fraction of diners using OT increases, restaurants increase their prices accordingly to recoup the costs of the platform. In models S8 to S10 (presented in table 8), we include the ratio of OT to Yelp reviews in the hazard models. As we have no information on OT reviews before 2010, we exclude all observations before 2010. In model S8 we repeat model S1 for this subsample. The results we obtain are qualitatively equivalent. OpenTable participation does not seem to have a significant effect on survival, and food rating is the only variable with a statistically significant coefficient estimate. In model S9, we introduce the Ratio OT/Yelp Reviews variable, along with the normalized count of reviews received in Yelp to account for popularity. The coefficient for the ratio of reviews variable is positive and significant. It implies that the probability of failure increases when a large fraction of guests use OT to make reservations. This is not what our model predicted, although it matches the complaints of restaurateurs against the platform. Although in our price analysis we determined restaurants raise their prices as the use of the platform by diners increases, this result suggests they may not be able to recoup all the costs of the platform. The coefficient for the number of reviews received in Yelp variable is negative and significant, implying that popular restaurants are less likely to fail. In model S10, we examine if restaurants in cuisines and locations with high OT adoption are affected in the same by increasing use of OT by diners as other establishments. To do so, we interact the Ratio OT/Yelp Reviews variable with the High Adoption by Restaurants in the Same Cuisine Within One Mile dummy. The coefficient estimate of the interaction is marginally significant, and almost exactly offsets the Ratio of OT/Yelp Reviews Coefficient. This implies that restaurants in cuisines and locations with high OT adoption are not affected by the fraction of guests that use OT to make their reservations. This may result from restaurants with most of their competitors participating in the platform being able to raise their prices more than other restaurants, and thus being able to recoup all the costs of the platform.

Overall, the relationship between OT participation and survival appears to be weak. We tested multiple specifications and only found statistically significant relations in limited cases. It seems that, if there is any effect, once OT adoption is high at competing restaurants, not participating in the platform could have a negative impact on survival. However, restaurants in low adoption locations and cuisines that acquire many of their diners through OT apparently have lower survival probabilities than other restaurants.

Table 7: Cox-Proportional Hazard Models S8-S10

	S8	S9	S10
OT	-0.0906	-0.0640	-0.0184
	(0.151)	(0.163)	(0.160)
Ratio OT/Yelp		0.169**	0.228***
		(0.0682)	(0.0621)
Ratio OT/Yelp x High Adoption 1M Same Cuisine			-0.235*
			(0.131)
High Adoption 1M Same Cuisine			0.169
			(0.216)
# Yelp Reviews		-0.961***	-0.953***
		(0.170)	(0.168)
Price	-0.00389	-0.0157**	-0.0160**
	(0.00777)	(0.00767)	(0.00771)
Price Sq.	4.98e-06	5.92e-05**	6.02e-05**
	(2.38e-05)	(2.36e-05)	(2.36e-05)
Service	-0.00170	-0.0208	-0.0207
	(0.0144)	(0.0205)	(0.0203)
Food	-0.0626***	-0.0465***	-0.0472***
	(0.0124)	(0.0160)	(0.0159)
Décor	-0.00808	0.0205	0.0180
	(0.0185)	(0.0156)	(0.0161)
Neighborhood F.E.	Yes	Yes	Yes
Cuisine F.E.	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes
Constant	-1.397	-0.508	-0.509
	(0.983)	(0.641)	(0.641)
Observations	4,078	4,078	4,078

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Discussion and Conclusions

In the last few years, online intermediaries have grown to occupy a central position in several markets. These platforms combine the opportunities that arise from leveraging connectivity and information, with the threats that can emerge from the central position and market power of platforms. We argue that to understand the net benefits new online intermediary platforms create in legacy markets, it is necessary to explicitly contrast the potential increases in market efficiency and gains from trade that result from the use of technology, with the incentives platforms introduce in the market for different stakeholders. We develop a simple analytical model to show how an intermediary platform that charges sellers and subsidizes buyers may be adopted by sellers, even if in the long term they would get no benefits from participating in the platform. We then test how the adoption of an online reservation platform in New York City, and its effects on prices and business survival, conform to our analytical model. We focused on the case of OpenTable (OT) in New York City (NYC), because OT is a long-lived platform that over the years has achieved remarkable levels of adoption. According to our model, the platform creates a prisoner's dilemma for restaurants. All restaurants have incentives to join OT to

poach customers from competitors or to protect its clientele. However, if all restaurants join, none of them gets additional customers. The platform increases the utility diners get from consumption, and restaurants pass down the costs of the platform to users through price increases but get no additional profits. As long as the costs of the platform are not greater than the benefit it gives to diners, its adoption will be welfare enhancing. To test the predictions of our model, we develop a database of restaurants' prices, participation in OT, and survival. Our empirical analysis supports the main features of our model: Adoption of OT by neighboring restaurants increased the probability of OT adoption; Once the platform achieved high levels of adoption, restaurants that participate in OT raised their prices in an amount equivalent to the cost they face from the platform; Finally, OT participation doesn't seem to have a positive effect on restaurants' survival. Below we discuss several aspects of our results including limitations, economic significance, welfare implications, implications for competition between platforms, and implications for other intermediaries and other online platforms.

OpenTable Adoption and Potential Demand Expansion

An assumption of our model that may seem too restrictive is that we consider that OT has no effect on increasing aggregate demand. We used this assumption to highlight that even in a scenario where restaurants don't expect to gain additional customers, they would still adopt the platform. Adapting the model to allow for the intermediary to increase aggregate demand is not hard, but it would not change the main mechanism behind the predictions of the model. We can consider the same model setup but assume that diners' utility is not high enough to ensure that everyone consumes. With this assumption, some diners will be too far away from the restaurants and will prefer not to buy. In this setting, the platform can increase demand as long as the additional utility it offers is high enough to get distant customers to buy. However, if the benefit offered by the platform is also high enough that it allows a restaurant that adopts the platform to poach customers from a non-adopting competitor, then the prisoner's dilemma will arise, and the end result will be similar to what we propose in section 3. The main change this modification would introduce is that restaurants would obtain some additional profits from OT participation thanks to the additional customers the platform adds. Thus, the key issue to consider is how much additional demand a platform like OT can introduce. By definition, the gains that may be obtained by reducing search cost and improving matching between preferences and services should be marginal. For the platform to increase demand, it is necessary to assume that the additional utility diners get from making reservations through OT is high enough to get consumers with low valuations to consume. In our perspective, it is not reasonable to expect that lowering search cost by offering a more expedient reservation system, and more information about the restaurant, would lead to a significant expansion of demand. If there was a big mass of unserved demand due to the difficulty of finding open reservations, that would have created opportunities for new entrants.

Empirically testing if the introduction of OT led to an expansion of aggregate demand for restaurants is an interesting problem, but it is out of the scope of this paper. However, by looking at some key statistics it doesn't seem plausible that OT adoption has resulted in an accelerated expansion of the restaurant industry in NYC. In general, OpenTable adoption is higher in metropolitan areas, and is particularly high in NYC. Thus, if OT makes people eat out more frequently, we should see the restaurant industry in NYC growing faster than the restaurant industry in the rest of the country. From figures reported in the Consumer Expenditure Survey of the Bureau of Labor Statistics we can see that, for the metropolitan statistical area of New York – Newark – Jersey City, expenditures in "food away from home" has stayed nearly identical in absolute terms in the last ten years (from 2006-2007 to 2016-2017) and has decreased relative to overall expenditure from 5.6% to 5.0%. In comparison, for all of the U.S., spending in "food away from home" has grown on average a 2% annually, increasing from 5.5% of overall expenditures to 5.6%. We can also compare New York's economic growth with restaurant openings in NYC. While the gross metropolitan product of the area has grown at an average compound annual rate of 2.2% (between 2008 and 2017), the total number of restaurants in NYC has grown at a 1.1% rate.

Endogeneity Concerns

An obvious concern with our empirical analysis is that the decision to adopt OT is endogenous and we rely on observational data. To test whether endogeneity affects our results, we tried three different strategies. Self-selection is probably a greater problem in the beginnings of OT, when only a few restaurants participated. It is easy to think of reasons of why early adopters could be different from the rest of the sample. However, towards the end of our sample over 70% of restaurants in the top price category, and over 50% of restaurants in the mid-price category participate in the platform. With such a broad adoption among restaurants that are likely to accept reservations, it is difficult to see how they could all be subject to unobservable characteristics that make them different from other restaurants. As we put together 12 years of panel data, covering a time period when OT adoption increased by a factor of 3.5, by using firm fixed effects in a difference-in-difference setup we are likely controlling for the most important sources of unobservable characteristics. In fact, in the price analysis' endogenous treatment effect models we cannot reject the null hypotheses that the error terms of the selection and the outcome regressions are uncorrelated. This wasn't the case in additional models we tried where we excluded restaurant fixed effects. This gives us some reassurance that the fixed effects are controlling for a large fraction of the self-selection issue. In the survival analysis, we could not employ restaurant fixed effects because they would not be identified. While in these models some coefficients related to OT adoption were significant, the estimated average treatment effect of OT participation was not. While we don't find an effect of OT participation on survival, we cannot rule out that OT may have a positive effect on profits. Survival is only an imperfect proxy of profits based on the assumption that non-surviving restaurants have negative profits. However, we cannot exclude the possibility that restaurants that lose money still survive. We may also be failing

to find an effect because OT participation only helps good performing restaurants, rather than restaurants that are struggling for survival. Lastly, even if we accept survival as a reasonable proxy for profits, it could also be the case that don't find an effect due to our data and identification strategy.

As the exclusion condition we used in the Heckman correction is not perfect, and the difference in difference analysis does not resolve all the endogeneity concern, we employed a third strategy to avoid endogeneity in our estimations. Instead of relying on restaurants' participation in the platform, we estimated the OT effect using the fraction of guests that make reservations through the platform. We obtain a proxy for this variable by comparing the number of reviews a restaurant gets in OT with the number of reviews it gets in Yelp. As restaurants have little control on how patrons' make reservations, this variable is less likely to suffer from the endogeneity concerns explained above. Our estimations show that restaurants with a greater share of guests booking trough OT exhibit higher price increases. We also find that restaurants that are not in high adoption neighborhood and cuisines, but that obtain many of their clients through OT, have lower survival rates than other restaurants.

Economic Significance of the Price Increase

It is interesting to consider whether the effects we observe are economically meaningful. At first sight, a $1 fee per guest seems irrelevant within the cost structure of a restaurant. However, if we consider how thin profit margins in the restaurant industry are, it is not hard to understand why restaurants pass down this cost to diners. According to figures from the Restaurant Industry Operations Report of the National Restaurant Association (2010), a restaurant with above median returns operates with a 5% net profit rate. This implies that for a restaurant with prices around the mean, the net profit per guest is only ~$2. If many guests start doing their reservations through OT, restaurants' profit could be severely affected. It is interesting to contrast this argument with OT's value proposition. According to a corporate presentation by OT (OpenTable, 2014), an incremental guest (in an average price restaurant) generates additional $27 in profits. OpenTable argues that most diners who book through the platform correspond to incremental business. This argument collides with some complaints by restaurateurs, who say OT does not bring much additional business, but instead takes over reservations that used to be completed by other means. We argue it is important to analyze where the incremental diners that OT offers are coming from. If those incremental diners are guests that would have dined at other restaurants (that are not on OT), then it is reasonable to expect those restaurants that are losing business will soon join OT to recoup lost customers, configuring the prisoner's dilemma our model highlights. Once many diners use OT to make reservations, and many restaurants participate in the platform, it will be hard for restaurants to restrict the number of tables available through the platform (or not to participate), as they would risk losing business to other restaurants with seats available in OT. As diners should always prefer to book through the platform, this should result in OT being used by most diners, and not only by incremental customers.

Welfare Implications

One of the predictions of the model is that OT will be welfare enhancing as long as the costs imposed by the platform are not greater than benefits users get from participating in it. To test this notion, we can use our estimations, figures reported by OT,[15] and statistics published by the National Restaurant Association. According to OT, on average each restaurant that participates in the platform seats 535 guests per month through the platform. Considering that in NYC there are 2,000 restaurants participating in OT, and that restaurants pay a monthly fee of $250 and per guest fee of $1, this implies that OT collects a total of ~$13 million in fees per year in NYC. According to figures from the National Restaurant Association, the median restaurant has 160 seats, and a median daily seat turnover of 0.8. If we consider the lowest price increase coefficient we obtained ($0.33), the price increase caused by OT results in additional ~$30 million paid by diners to restaurants. Note that the price increase is paid by all diners, not only by those that use OT. According to this crude estimation, restaurants would be collecting more money than what they are paying out in fees to OT. However, it is likely that the number of guests seated per restaurant by OT in NYC is higher than the OT's overall average. In fact, the figures used above imply that only 14% of guests book through OT. This figure seems low as, for example, 56% of Zagat surveyors reported they typically make reservations online (Zagat 2014, pp. 5). If this number is higher for NYC, then the additional revenues collected by restaurants and the fees paid to OT would be closer to each other. To evaluate the benefits that diners get from OT we can consider that an average restaurant reservation includes 3 guests. This would imply that OT processes on average 178 reservations per restaurant per month. For each reservation, the consumer gets $1 in rewards. If all rewards are redeemed, this implies diners get back ~$4 million dollars in rewards per year. Comparing this figure to the $30 million paid through price increase leaves ~$26 million unaccounted for. If we consider that, besides rewards, the only additional benefit diners get from using OT to make a reservation is time saved, and the average hourly rate in the U.S. is $25/hour, to create $26 million in time savings each reservation done through OT would need to save ~15 minutes. This figure is not easy to achieve, but it is also not impossible, especially considering that the hourly wage of people that eat out in NYC is likely higher than the US average, and that OT likely contribute to users' welfare with more than just rewards and time saved. These simple back of the envelope calculations suggest that OT may be welfare enhancing, and that additional revenues collected by restaurants through price increases are in the same order of magnitude of the fees restaurants pay to OT.

Implications for Competition Between Platforms

Over the years, many competitors have tried to displace OT. It is tempting to assume none of these challengers were successful due to the importance of network externalities, and the advantage OT gained by being the first

[15] OpenTable Global Fast Facts (Q22017). Available at: http://files.shareholder.com/downloads/ABEA-4SW9EX/5505156029x0x394755/ed27a649-cf4e-401f-af22-b724c184608a/OpenTable_Fast_Facts.pdf

significant entrant. However, even platforms with a large base of users have had limited success in their bids to displace OT. Most notably Yelp added in 2010 a reservation feature. Initially, the feature relied on OT, but in 2013 Yelp acquired a competing reservation platform and ended its agreement with OT shortly after. Even though Yelp is one of the most famous review platforms, it hasn't managed to position itself as a serious competitor to OT. It is not until the last years of our sample that some challengers started having some success in eroding OT's popularity. These platforms, rather than trying to replicate OT's model as early contenders did, took better advantage of market dynamics in their design. For example, platforms such as Resy (a reservation platform created in late 2014 and acquired by AirBnb in 2017), instead of always providing diners with free reservations started offering a "ticket" system. As available tables in popular restaurants are a scarce good, what these platforms do is to offer restaurants the ability to sell, or even in some cases auction, vacant tables when availability is low. Instead of making a free reservation, diners in these platforms sometimes can "buy tickets" to dine at coveted places. This effectively changes the dynamics explained in this study. By eliminating rewards, it removes some of the incentives diners have to overuse the platform. To keep users interested in participating in the platform, they compensate for this loss by offering access to exclusive and hard to book restaurants in exchange of a fee.

Relation with Other Intermediaries

Our empirical results provide interesting evidence supporting theoretical contributions that explore how intermediaries may manipulate the price each side of the platform face to influence demand for its services. For example, Edelman and Wright (2015b) develop a model in which an intermediary that enforces price coherence can profitably increase demand for its services, which in turn leads to inflated prices and could result in welfare losses. This has been a common concern in the context of credit card rewards programs, its effects on interchange fees, and ultimately on products' prices. However, testing how interchange fees affect prices is unfeasible due to the vast nature of credit card use. In contrast, our setup provides an ideal setting to analyze how increased adoption of an intermediary influenced prices. We documented adoption of an intermediary platform practically since it was introduced until it was used by most of the target market. By relating price changes with increasing adoption of the intermediary, we could establish a relationship between adoption and price increases. A common concern in this theoretical literature has been whether intermediaries lead to decreased consumer surplus. While we cannot provide a definite answer, our results suggest OT's costs and benefits are likely close to each other. However, it is important to note that adoption of the intermediary has re-distributional implications. OpenTable's costs are shared by all diners of restaurants that adopt the platform, while its benefits are only enjoyed by patrons that use OT.

Implications for Other Online Platforms

We purposely chose to study a market where the intermediary is not significantly changing the way the industry operates. The advantage of this strategy is that we can clearly isolate the effect of the intermediary. The disadvantage is that our results cannot be directly applied to other platforms that significantly change how their respective industries operate. For example, Uber and Lyft not only serve as a platform connecting two sides of a transaction but they also, thanks to their design, effectively increase the number of "drivers" available and the cost structure of the service. For this type of platforms, our results still highlight the importance of contrasting the gains that result from the technology, with the incentives introduced by the platforms' design. For example, in ride-sharing platforms, it is important to ponder if the price advantage they offer is due to the ability of the platform to reduce idle time by efficiently matching drivers to riders, or if it originates from finding drivers that are willing to work for a lower wage. There are many platforms whose main contribution is to increase the efficiency of existing relations. For example, we believe the online targeted advertising ecosystem may be configuring a similar prisoner's dilemma setting. This is an interesting industry to explore, as in 2016 over 70 billion dollars were spent on digital advertising (IAB, 2017). While early adopters of targeted advertising may benefit from the technology, it is unclear if these gains will subsist after most advertisers follow suit. If OpenTable is any indication, gains will erode over time and buyers could end up bearing the costs of the technology.

References

Armstrong, M., 2006. Competition in two-sided markets. *The RAND Journal of Economics*, 37(3), pp.668-691.

Anderson, C. 2006. The Long Tail.

Benkler, Y. 2004 "Sharing nicely: On shareable goods and the emergence of sharing as a modality of economic production." *Yale Law Journal*, 273-358.

Berger, T., Chen, C., & Frey, C. B. (2018). Drivers of disruption? Estimating the Uber effect. European Economic Review.

Brown, J. R., and Goolsbee, A. 2002. Does the Internet make markets more competitive? Evidence from the life insurance industry. *Journal of political economy*, 110(3), 481-507.

Brynjolfsson, E., Hu Y., and Simester 2011. Goodbye pareto principle, hello longtail: The effect of search costs on the concentration of product sales. *Management Science* 57(8), 1373–1386

Brynjolfsson, E., and Smith, M. D. 2000. "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science*, (46:4), pp. 563–585 (doi: 10.1287/mnsc.46.4.563.12061).

Caillaud, B., and Jullien, B. 2003. "Chicken & Egg: Competition among Intermediation Service Providers," *The RAND Journal of Economics*, (34:2), pp. 309–328.

Calo, R., & Rosenblat, A. (2017). The taking economy: Uber, information, and power. Columbia Law Review, 1623-1690.

Chen, M. K., Chevalier , J. A., Rossi, P. E., and Oehlsen, E. 2017. "The Value of Flexible Work: Evidence from Uber Drivers." *Working Paper 23296. National Bureau of Economic Research.* https://doi.org/10.3386/w23296.

Cherry, M. 2016. "Beyond Misclassification: The Digital Transformation of Work," *Comparative Labor Law & Policy Journal (37)*

Cohen, P., Hahn R., Hall J., Levitt, S., and Metcalfe, R. 2016. "Using Big Data to Estimate Consumer Surplus: The Case of Uber." *Working Paper 22627. National Bureau of Economic Research.* https://doi.org/10.3386/w22627.

Edelman, B., and Wright, J. 2015a. Markets with Price Coherence. HBS Working Paper 15-061.

Edelman, B., and Wright, J. 2015b. "Price Coherence and Excessive Intermediation." The Quarterly Journal of Economics 130 (3):1283–1328. https://doi.org/10.1093/qje/qjv018.

Fraiberger, S., and Sundararajan A. 2017. "Peer-to-Peer Rental Markets in the Sharing Economy." *SSRN Scholarly Paper ID 2574337. Rochester, NY: Social Science Research Network.* https://papers.ssrn.com/abstract=2574337.

Goldfarb, A., & Tucker, C. (2017). Digital economics (No. w23684). *National Bureau of Economic Research.*

Hall, J.V., and Krueger A. B. 2016. "An Analysis of the Labor Market for Uber's Driver-Partners in the United States." *Working Paper 22843. National Bureau of Economic Research.* https://doi.org/10.3386/w22843.

Hayashi, F. 2009. "Do US consumers really benefit from payment card rewards?," *Economic Review-Federal Reserve Bank of Kansas City*, (94:1), p. 37.

Holford, T. 1980. "The Analysis of Rates and of Survivorship Using Log-Linear Models." *Biometrics*, 36: 299-305.

IAB Internet Advertising Report. Technical report, IAB, June 2017.

Kroft, K., and Pope, D. G. 2014. "Does Online Search Crowd Out Traditional Search and Improve Matching Efficiency? Evidence from Craigslist," *Journal of Labor Economics*, (32:2), pp. 259–303.

Laird, N., and D. Oliver.1981. "Covariance Analysis of Censored Survival Data Using Log-Linear Analysis Techniques." *Journal of the American Statistical Association*, 76:231-240.

Lobel, O. 2016. "The law of the platform." *Minnesota Law Review 101: 87*.

National Restaurants Association 2010. Restaurant Industry Operations Report.

National Restaurants Association 2018. New York Restaurant Industry at a Glance. (Available at: https://www.restaurant.org/Downloads/PDFs/State-Statistics/NewYork.pdf)

OpenTable 2014. "Corporate Presentation", (Available at: http://files.shareholder.com/downloads/ABEA-2TKK09/0x0x750629/09e2ff42-91ea-4b5f-845e-350faecc8fd0/OpenTable%20Corporate%20Presentation%20(Q1%202014)%20FINAL.pdf)

Orlov, E. (2011). How does the internet influence price dispersion? Evidence from the airline industry. *The Journal of Industrial Economics,* 59(1), 21-37.

Pollman, E. and Barry, J. M., 2017 "Regulatory Entrepreneurship" *Forthcoming in Southern California Law Review*. (Available at SSRN: https://ssrn.com/abstract=2741987)

Prager, R., Manuszak, M., Kiser, E., and Borzekowski, R. 2009. Interchange Fees and Payment Card Networks: Economics, Industry Developments, and Policy Issues. Finance and Economics Discussion Series Working Paper 2009-23.

Rochet, J.-C., and Tirole, J. 2003. "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association*, (1:4), pp. 990–1029 (doi: 10.1162/154247603322493212).

Rochet, J.-C., and Tirole, J. 2006. "Two-Sided Markets: A Progress Report," *The RAND Journal of Economics*, (37:3), pp. 645–667.

Rosenblat, A. 2016. "What Motivates Gig Economy Workers." *Harvard Business Review (Nov. 17, 2016)*, (available at: http://hbr.org/2016/11/what-motivates-gig-economy-workers)

Rosenblat, A. and Stark, L. 2016. "Algorithmic Labor and Information Asymmetries: A Case Study of Uber's Drivers." *International Journal of Communication, 10, 27*.

Rysman, M., and Wright, J. 2014. "The economics of payment cards." *Review of Network Economics* 13.3: 303-353.

Schuh, S. D., Shy, O., and Stavins, J. 2010. "Who gains and who loses from credit card payments? Theory and calibrations," (available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1652260).

Seamans, R., and Zhu, F. 2014. "Responses to Entry in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers," *Management Science*, (60:2), pp. 476–493 (doi: 10.1287/mnsc.2013.1785).

Tomassetti, J. "Does Uber Redefine the Firm: The Postindustrial Corporation and Advanced Information Technology." *Hofstra Labor and Employment Law Journal,* 34: 1.

Waldfogel, J. and L. Chen (2006). Does information undermine brand? Information intermediary use and preference for branded web retailers. *Journal of Industrial Economics* 54(4), 425–449.

Yang, H. (2013). Targeted search and the long tail effect. *The RAND Journal of Economics* 44(4), 733–756.

Zagat Survey (2014). *2014 New York City Restaurants*

Zervas, G., Proserpio, D., and Byers, J. W. 2017. "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry," *Journal of Marketing Research* (doi: 10.1509/jmr.15.0204).

Zettelmeyer, Florian, F. S. M. and J. Silva-Risso (2001). Internet car retailing. *Journal of Industrial Economics* 49(4), 501–519.