# Online intermediation in legacy industries: The effect of reservation platforms on restaurants' prices and survival 

By Cristobal Cheyre and Alessandro Acquisti *

Preliminary. Date of this draft: January 2022

We study the impact of increasing online intermediation in legacy industries. We motivate the empirical analysis with a duopoly model where an intermediary platform enables firms to attract consumers by offering them higher benefits. We show that firms adopt the platform even when they cannot expect benefits from joining, because as platform popularity rises, it extracts a growing proportion of the benefits it creates. The analysis focuses on restaurants' adoption of OpenTable in New York City. Results support the model predictions of cost pass-through to consumers of fees charged to restaurants, and no effect of adoption on restaurant survival.

JEL Codes: L11; L86; D22; D40

[^0]Online platforms are increasingly mediating traditionally offline direct transactions between firms and consumers. Examples include hotel and restaurant reservations, car-sharing services, and apartment rentals. Online platforms can increase efficiency and create gains from trade through economies of digitization (Goldfarb and Tucker 2019). However, theoretical modeling shows that intermediation can lead to inflated prices and reduced consumer surplus (Edelman and Wright 2015). In theory, it is even possible that agents in bilateral interactions may accept the entry of a third-party intermediary that only extracts surplus from them (Spiegler 2000). These models raise concerns over the consequences of online intermediation on the allocation of economic welfare. To date, however, empirical tests of the welfare impact of online intermediaries have been limited. We provide novel evidence on the impact of the increasing adoption of an online intermediary platform on actors in a legacy industry. We focus on the restaurant industry and the emergence of online reservation platforms - an example of an intermediary interjecting itself in a previously direct relationship. We show how the increasing popularity of a dominant reservation system led to higher restaurant prices but had no positive effect on restaurants' survival.

We motivate our analysis with a Hotelling style model in which a new intermediary platform can induce a prisoner's dilemma that leads both sellers to adopt it, even if they cannot expect any benefits from doing so. The platform helps sellers attract consumers by offering higher utility (for example by reducing search and transaction costs) to buyers that use it. If the platform allows an adopter to capture customers from a non-adopting competitor and obtain higher profits in this way, it creates incentives for both sellers to adopt. Initially, when its popularity is low, the platform can only charge a fraction of the benefits it creates to sustain the prisoner's dilemma. However, as its popularity grows, it can raise its fees until it extracts all the benefits it creates. If both sellers adopt, they will pass through all
the costs of the platform to consumers through price and obtain no additional profits.

For the empirical analysis we exploit the rapid rise of restaurant reservation platforms in the early 2000s and the long-term dominance of OpenTable (OT) in this space. We compile 12 years of panel data on restaurant prices, survival, and OT adoption in New York City. During this period OT adoption increased by a factor of $\sim 3.5$. This allows us to observe most restaurants in the sample before and after they adopt OT. We employ multiple measurement and identification strategies and find a remarkably consistent effect of OT adoption on prices: after OT becomes dominant, restaurants that adopt it raise their prices, by an amount we estimate to be roughly equivalent to the diner fee that OT charges to restaurants per guest. We do not observe any consistent or statistically significant effect of OT participation on participants' likelihood of survival, which suggests that there is no strong effect of adoption on profits. Consumers who do not use the platform to make reservations suffer welfare losses, as they subsidize the costs of the platform, via higher prices, for those who do use it. For consumers who do use the platform, whether its net impact is welfare enhancing or depressing depends on their valuation of the benefits (such as lower transaction costs) of reserving through it.

Our research contributes to an emerging literature that explores the impact of online platforms in the economy, and their consequences for consumers' and incumbents' welfare. While some attention has been devoted to online platforms and their consequences for the industries they disrupt, most work has focused on platforms that arrange for alternative ways of providing goods and services to substitute incumbents (Seamans and Zhu 2014; Kroft and Pope 2014; Zervas, Proserpio, and Byers 2017; Einav, Farronato, and Levin 2015; Farronato and Fradkin 2018). Our focus, instead, is on online platforms that have started intermediating transactions between consumers and incumbents in legacy industries, and that co-exist with traditional means of conducting business. While
these platforms may, at first glance, appear less disruptive than counterparts that change the way in which some industries operate (such as ride-sharing platforms like Uber and apartment-sharing platforms like Airbnb), their aggregate impact is significant and widespread, as they are increasingly being deployed in different industries. With the proliferation of mobile devices, recommender systems, and automated personal assistants, this type of intermediation is poised to become prevalent.

When using this type of intermediary platforms, consumers receive the same product/service they would receive otherwise, but sellers experience a different payment scheme, with fees that appear modest at first but rise to staggering amounts once most sales are completed through the intermediary. Examples include users making restaurant reservations through online platforms rather than by directly contacting the restaurant; consuming news on the home screen of their smartphone or in a news aggregator rather than by going to the publishers' webpages; completing supermarket or restaurant purchases using a delivery service; or even searching on a search engine for the page they are going to visit and clicking on a sponsored link rather than visiting the page directly. In all these cases, sellers pay high fees to the intermediary. With restaurant reservation platforms, restaurants typically pay a per-guest fee to the platform. Delivery services often charge staggering fees to restaurants or supermarkets, as high as $30 \%$. When news is consumed through aggregators, such as Google's AMP, outlets only receive a fraction of the advertising revenues that the same content would generate on their own page. With sponsored search results, advertisers have to pay per click, even when the key term may be their own brand. Our model and results suggest that these settings configure prisoner's dilemmas for legacy players, and that the equilibrium strategy is for all sellers to adopt the intermediary and pass down the fees to consumers through price.

The rest of the paper is organized as follows. After discussing related work in the next subsection, in Section I we present the model that provides the motivation for our analysis. Section II presents an overview of OT and the restaurant industry in NYC. Section III describes the construction of our dataset and provides summary statistics. In section IV we present the analysis of the impact of OT on restaurants' prices and in section V the impact of OT on restaurants' survival. We discuss implications and conclusions in section VI.

## A. Related Work

Our work is related to studies that have explored the influence of platforms and two-sided markets across different contexts. First, our results contribute to a growing literature on digital platforms and their implications for various stakeholders. Several early works analyzed the effects of digital markets on search and matching. A rich body of work has examined how the reduction of search costs introduced by digital markets affects prices (Brynjolfsson and Smith 2000; Brown and Goolsbee 2002; Morton, Zettelmeyer, and Silva-Risso 2001; Orlov 2011), brand differentiation (Waldfogel and Chen 2006), and product variety (Yang 2013; Anderson 2006; Brynjolfsson, Hu, and Simester 2011). More recent works have focused on particular economic features and dynamics brought about by online platforms. Edelman and Luca (2014) show that non-black hosts on Airbnb charge higher prices than black hosts for seemingly equivalent accommodations. Luca (2016) explores the impact of Yelp average ratings on revenues. Closer to our focus, some researchers explore the impacts of online platforms on participants and on displaced incumbents. Zervas et al. (2017) show how Airbnb negatively impacted hotels' occupancy rates and prices in Texas. Farronato and Fradkin (2018) explore the welfare implications of Airbnb in New York City for travelers, hosts, and hotels. Seamans and Zhu (2014) show how Craigslists caused a sharp drop in sales of
classified ads by newspapers, and Kroft and Pope (2014) show how Craigslists led to a decrease in rental and home vacancies. We contribute to this literature by focusing on a different type of platforms that have started intermediating what used to be, traditionally, offline transactions. This is an increasingly important group of platforms, as technological advances push towards digital intermediation on all types of transactions. Our findings support theoretical concerns over sellers' disadvantages arising from way fee structures frequently imposed by these platforms.

Our results are also interesting to contrast with the literature on cost passthrough. Theoretically, firms in competitive markets will pass most, or all, of cost changes to consumers, while firms in less competitive markets will only pass a fraction of these changes (Bulow and Pfleiderer 1983). The restaurant industry is recognized as overly competitive with thin margins. Empirical works that have studied the effect of cost shocks in the restaurant industry have found a large degree of cost pass-through (Allegretto and Reich 2018; Cawley et al. 2018), even for small cost increases. Cawley et al. (2018) found that after a tax on sugar-sweetened beverages was established in Boulder, CO, restaurants passed $69.4 \%$ of the new tax to consumers. Observing that after adopting OT restaurants increase their prices in an amount that resembles the fees charged by the platform suggests that restaurateurs view OT as a cost, rather than a source of gains that would materialize by attracting additional diners.

Finally, our results provide complementary empirical evidence to a related, long-standing debate regarding the welfare consequences of intermediation fees in credit card networks. Just as merchants cannot charge more to consumers paying with credit cards, restaurants cannot charge more to consumers who use OT to make reservations. Theoretical contributions have explored whether the fee structure of credit card networks introduces distortions in the market and is biased against merchants (Edelman and Wright 2015; Wright 2012). Empirical work on credit
card usage is complicated by their vast adoption and lack of variation for identification purposes. In our setting we observe a new platform almost from its introduction until it becomes prevalent in its industry, providing us with rich heterogeneity that allows us to employ different identification strategies. Our results suggest that fees negatively affect merchants, who in our setting were able to pass the cost down to consumers.

## I. Model of Intermediation in Legacy Industries

To motivate our empirical analysis, we develop a model with two sellers faced with the decision to adopt a new intermediary. The goals of the model are to explore under which conditions sellers will adopt an intermediary platform, to explore the influence of the platform's popularity among consumers on this decision, and to determine the consequences of adoption on prices and welfare. We do not model interactions between pricing structures or network externalities - Rochet and Tirole (2006) and Armstrong (2006) provide models that explain usage externalities and/or membership externalities under different settings. Instead, we take as given that the intermediary will charge all fees to sellers and prohibit them from charging a higher price to intermediated buyers - which is the fee structure used by many online platforms mediating transactions in legacy markets. In a theoretical contribution, Edelman and Wright (2015) describe this pricing structure in detail and explain why it is convenient for the intermediary. While the results of our model are similar to their predictions in regards to prices and welfare outcomes, our model is distinct in its focus on exploring the sellers' adoption decision, and in demonstrating how the portion of the created benefits that the intermediary can extract increases as the intermediary becomes more popular.

Consider a Hotelling model in which two sellers ( $a$ and $b$ ), selling a differentiated good, 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 sellers are located at opposing ends of the unit line. ${ }^{1}$ A consumer that is located at a distance $x$ from a seller and buys one unit from it obtains a utility $\mu$ and incurs a transportation cost of $t x^{2}$. We assume that $\mu$ is high enough that, in all scenarios considered, all consumers buy one unit from one of the two sellers. We interpret the location of consumers as their preferences towards products' variations, and the transportation cost as the disutility of consuming a unit different from their preferred variety. In the case of a restaurant, for example, this could be a combination of preferred location and cuisine type.

Assume that an innovator offers a technology to sellers that will increase the utility for its customers by $\rho$ if adopted. This additional utility could be in the form of decreased search and/or transaction costs incurred when using the intermediary (in the case of restaurants, this could correspond to time saved when making reservations online and/or finding a better match). The innovator acts as an intermediary and only increases the utility of those consumers who buy through it. Sellers cannot charge a differential (higher) price to consumers who use the intermediary. This is a typical condition imposed by intermediaries, referred to in the literature as "price coherence" (Frankel 1998; Edelman and Wright 2015). With price coherence, any consumer who is aware of the technology should use it when buying from an adopter, as the price is the same and the intermediary provides added utility. We assume that a fraction $\alpha$ 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 the technology is a monopoly platform that sets a price $c$ per unit - i.e., sellers incur a cost $c$ for each consumer who uses the intermediary. At time 1 of the model each seller

[^1]decides whether to adopt the technology or not; at time 2 each seller sets its price $P_{i}$ and customers choose to buy one unit from their preferred seller. To find the pure strategy Nash equilibrium of the model, we consider the four possible scenarios that could result: no adoption, two scenarios of partial adoption (in which either firm adopts), and full adoption.

We first consider the "no adoption" scenario, in which neither seller adopts the technology. In this case, which simply corresponds to a standard Hotelling model with quadratic transportation costs, sellers split the market in half, and each get the same profits. The price, demands, profits, and consumer surplus in this scenario are:

$$
P_{a}=P_{b}=t, X_{a}=X_{b}=\frac{1}{2}, \pi_{a}=\pi_{b}=\frac{t}{2}, C S=v-t-\frac{t}{12}
$$

We next consider the "full adoption" scenario, in which both sellers adopt the platform. In this case, we need to distinguish between consumers who are aware of the platform (informed consumers) and those who are not (uninformed consumers). In this case sellers still split demand in half, but they now have to pay a fee for each consumer that uses the platform (for each informed consumer). The utility for seller $i$ is $\pi_{i}=\left(P_{i}-c\right) X_{I i}+P_{i} X_{U i}$, where $X_{I i}$ represents the demand from informed consumers for seller $i$ and $X_{U i}$ the demand from uninformed consumers. The prices, overall demand, profits, and consumer in this scenario are:

$$
P_{a}=P_{b}=t+\alpha c, X_{a}=X_{b}=\frac{1}{2}, \pi_{a}=\pi_{b}=\frac{t}{2}, C S=v-t-\frac{t}{12}+\alpha(\rho-c)
$$

In this full adoption scenario, sellers will split the market in half, and will obtain the same profits as in the no adoption scenario. Customers will face higher prices, as sellers pass down the costs of the platform. The higher the number of customers who know about and use the platform (as represented by $\alpha$ ), the higher prices will be. There are a few interesting aspects to note regarding consumer
surplus under this scenario. The first is that when awareness about the platform is incomplete, uninformed consumers will be worse off than in the no adoption scenario, as under full adoption they are receiving the same utility as in the no adoption case but pay higher prices. Aggregate consumer surplus will depend on how the price of the platform is set. If $\rho>c$, aggregate consumer surplus will be higher. If the platform sets its price at $\rho$, it will extract all the benefits it creates, and consumer surplus will be the same as in the no adoption scenario. Note that in this case informed consumers will be better off than uniformed consumers, as the benefits of the platform are only enjoyed by those who use it, while the costs are shared by all consumers. How high the platform can set its price is determined by the partial adoption scenario, as the platform needs to choose a price that creates incentives for the sellers to join the platform.

The two remaining scenarios are "partial adoption" scenarios, in which either of the sellers adopts. Let's assume that seller $a$ decides to adopt and seller $b$ does not (the other case is analogous). In this case, the demands each of the sellers faces are:

$$
\begin{aligned}
& X_{a}=X_{I a}+X_{U a}=\alpha\left(\frac{1}{2}+\frac{P_{b}-P_{a}}{2 t}+\frac{\rho}{2 t}\right)+(1-\alpha)\left(\frac{1}{2}+\frac{P_{b}-P_{a}}{2 t}\right) \\
& X_{b}=X_{I b}+X_{U b}=\alpha\left(\frac{1}{2}+\frac{P_{a}-P_{b}}{2 t}-\frac{\rho}{2 t}\right)+(1-\alpha)\left(\frac{1}{2}+\frac{P_{a}-P_{b}}{2 t}\right)
\end{aligned}
$$

Intuitively, the seller that adopts the platform will capture some additional (informed) customers at the expense of the non-adopter due to the benefits offered by the platform to consumers. There will also be a transfer of demand due to the prices set by each seller. The adopter will want to charge a higher price as it faces added demand from informed consumers. The non-adopter will want to lower its
price to capture additional uninformed consumers and compensate for the loss of informed consumers. The optimal prices and resulting demands are: ${ }^{2}$

$$
\begin{array}{ll}
P_{a}=t+\frac{2}{3} \alpha c+\frac{1}{3} \alpha \rho, & X_{a}=\frac{1}{2}+\frac{1}{2 t}\left(\frac{\alpha \rho}{3}-\frac{\alpha c}{3}\right) \\
P_{b}=t+\frac{1}{3} \alpha c-\frac{1}{3} \alpha \rho, & X_{b}=\frac{1}{2}-\frac{1}{2 t}\left(\frac{\alpha \rho}{3}-\frac{\alpha c}{3}\right)
\end{array}
$$

The profits for each seller are:

$$
\begin{gathered}
\pi_{a}=\left(t+\frac{2}{3} \alpha c+\frac{1}{3} \alpha \rho\right)\left(\frac{1}{2}+\frac{1}{2 t}\left(\frac{\alpha \rho}{3}-\frac{\alpha c}{3}\right)\right)-\alpha c\left(\frac{1}{2}+\frac{\rho}{2 t}-\frac{\alpha c+2 \alpha \rho}{6 t}\right) \\
\pi_{b}=\left(t+\frac{1}{3} \alpha c-\frac{1}{3} \alpha \rho\right)\left(\frac{1}{2}-\frac{1}{2 t}\left(\frac{\alpha \rho}{3}-\frac{\alpha c}{3}\right)\right)
\end{gathered}
$$

To give firm $a$ incentives to join the platform, the intermediary must set its price $c$ at a level such that firm $a^{\prime} s$ profits are at least $t / 2$. This happens when:

$$
c \leq \frac{6 t+9 \rho-7 \alpha \rho}{2 \alpha}-\sqrt{\left(\frac{7 \rho}{2}-\frac{9 \rho}{2 \alpha}-\frac{3 t}{\alpha}\right)^{2}-\rho^{2}-\frac{6 t \rho}{\alpha}}
$$

This condition implies that when all consumers are aware of the platform ( $\alpha=1$ ), the intermediary can set a price of up to $\rho$, which is the total of the benefits it provides to consumers. When $\alpha$ is lower than 1 , the platform can only charge a fraction of the benefits it provides to consumers. If the platform sets its price in such a way that, under the partial adoption scenario, the adopting firm makes profits of at least $t / 2$, a prisoner's dilemma arises. The best response for each seller to whatever decision the other seller takes is to adopt the platform. Adopting the platform will not increase the profits of sellers if they both adopt, but is nonetheless

2 For simplicity, we assume that t is high enough that the demand from informed and uniformed consumers that each seller faces is greater than or equal to 0 . This is $t \geq \operatorname{Max}\left[\left(\frac{1}{3} \alpha c+\frac{2}{3} \alpha \rho\right),\left(\rho-\frac{\alpha c}{3}-\frac{2}{3} \alpha \rho\right)\right]$.
the best strategy to poach customers from competitors (in the partial adoption scenario), or to protect customers from getting poached (in the full adoption scenario). Thus, the pure strategies Nash equilibrium is for both sellers to adopt.

It is interesting to analyze what happens to profits and consumer surplus in the partial adoption scenario. When $\alpha$ is less than 1 , assuming the platform is setting its price as explained above, the aggregate profits will be less than in the no adoption and full adoption scenarios. While the adopter (firm $a$ ) will obtain higher (or the same) profits as in the other cases, the non-adopter (firm b) will make fewer profits. This happens because firm $b$ loses customers to firm $a$ and the only way it can recover some of the loss in revenue is by lowering its price to regain some informed consumers or capture uninformed consumers from firm $a$. However, lowering prices reduces the profitability of each of its remaining consumers, a problem that is compounded by the quadratic transportation cost that makes this strategy costly. Consumer surplus will be equal to or higher than in the no adoption and full adoption scenarios. If $\alpha$ is equal to 1 and the platform sets the price at $\rho$, consumers will obtain the same surplus as in the no adoption scenario. If $\alpha$ is less than 1, consumer surplus will be higher. Informed consumers buying from firm $a$ will benefit from the additional utility provided by the platform, while uniformed consumers buying from firm $b$ will benefit from lower prices. However, uniformed consumers buying from firm $a$ will be worse off as they do not enjoy the benefits of the platform and are too far from firm $b$ to benefit from its lower price.

An interesting extension to our model would be to consider under which conditions an intermediary platform could increase the demand for both sellers. For this to happen, it would be necessary that without the intermediary there are consumers that are not buying a unit, because they are too far from either seller. In our model, this implies there is a mass of unmet demand in the center of the linear city. In the case of restaurants, this could happen, for example, if some consumers
decide not to eat out because it is too difficult to find a reservation in a restaurant of their liking. Two insights can be drawn from this observation: This mass of consumers cannot be too big, as otherwise new sellers would enter to serve this unmet demand. Additionally, the prisoner's dilemma outlined in our model will still arise as long as the platform allows a seller to poach consumers from the competitor, which should be the case if the unmet demand is not large.

## II. OpenTable and the Restaurant Industry in New York City

OpenTable started in 1998 after its founder, Chuck Templeton, reportedly witnessed his wife spend hours on the phone trying to secure a reservation. OT 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 during the time we study, restaurants paid a setup fee of around US\$700 (varying 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. ${ }^{3}$

During its long life, OT has developed loyalty among diners, and while it has attracted open criticism from some restaurateurs, its adoption rate has been remarkable. In the early 2000s, only a couple hundred restaurants participated in the platform in NYC. The figure grew to $\sim 2,000$ restaurants by 2014. The value proposition OT presents to restaurant owners is straightforward, but its true contribution hinges on how users decide to use the platform. OpenTable is marketed to restaurants as a way to allow them to fill additional tables that would normally go unused, easily justifying the fee. While restaurants would prefer to use OT only
for seats that usually go unused, some existing diners will prefer to book through OT as it is more convenient than other alternatives and it gives them rewards. This tension has been featured numerous times in national media. For example, 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. ${ }^{4}$ 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." San Francisco restaurateur Mark Pastore explained on his restaurant's webpage why he thought OT was a poor bargain for restaurant owners. The post gained notoriety and sparked notes in 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 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 restaurateur starts resenting the fees, he feels locked into the platform as he fears losing most of his clientele if he parts ways with OT.

The anecdotal accounts presented above closely match the prisoner's dilemma proposed by our model and our predicted null effect of the platform on restaurants' profitability. What at first sight may seem inconsistent with our model is that OT has not raised its $\$ 1$ per guest fee since its inception. However, this is misleading in two ways. OpenTable did heavily subsidize the installation costs of the platform in its first few years. While it charged only $\sim \$ 500$ for the installation of the OT
terminal, its average costs were closer to $\sim \$ 5,000$, and sometimes much higher because, when OT started, restaurants were not typically equipped to install computer terminals at the host stand and required extensive remodeling to do so. ${ }^{6}$ Additionally, in 2003 OT started offering restaurants the ability to promote 1,000points tables, ${ }^{7}$ which provide diners with 10x higher rewards, but cost restaurants $\$ 10$ per guest rather than just $\$ 1$ per guest. This effectively raises the average fee paid by restaurants to OT per guest.

## III. Data

We rely on three sources of data for the empirical analysis: the NYC Department of Health and Mental Hygiene (DOHMH) restaurant inspection database, which we use to infer restaurants' survival; historical captures of OpenTable's website stored on the Internet Wayback Machine, which we use to obtain OT participation; and data compiled from the Zagat survey, to obtain prices and ratings. We also collect all Yelp reviews received by restaurants in our sample - an additional measure of restaurants' popularity.

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. ${ }^{8}$ We use inspections' data to compile 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 inspections through July 2017.

[^2]Table 1: Data Description

|  | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Cost | 35.6 | 35.9 | 37.4 | 38.8 | 40.9 | 41.1 | 41.1 | 42.6 | 42.3 | 43.6 | 45.6 | 45.3 |
| Food Rating | 20.3 | 20.6 | 20.7 | 20.7 | 20.7 | 21 | 21.4 | 21.2 | 22.5 | 22.3 | 22.7 | 22.5 |
| Décor Rating | 15.8 | 15.9 | 15.9 | 15.9 | 15.9 | 16 | 16.4 | 16.4 | 17.8 | 17.3 | 17.5 | 17.9 |
| Service Rating | 17.6 | 18 | 17.9 | 17.9 | 17.9 | 18.4 | 18.8 | 18.9 | 20 | 19.5 | 19.6 | 20 |
| OT Participation ( Nr of Rest) | 222 | 291 | 381 | 458 | 529 | 607 | 687 | 813 | 857 | 888 | 886 | - |
| In Zagat at Time t | 1934 | 1987 | 2002 | 2067 | 2070 | 2061 | 2109 | 2104 | 2115 | 2075 | 2136 | 2232 |
| In Zagat at Time t and $\mathrm{t}-1$ | - | 1631 | 1674 | 1726 | 1789 | 1717 | 1747 | 1758 | 1703 | 1837 | 1630 | 1763 |
| Matched to DOHMH | 1292 | 1422 | 1517 | 1652 | 1704 | 1716 | 1776 | 1800 | 1804 | 1791 | 1871 | 1949 |
| Exits (Last Inspection in Year $<=\mathrm{t}$ ) |  |  |  | 41 | 97 | 111 | 115 | 136 | 172 | 189 | 190 | 231 |
| Nr. Rest. with Yelp Reviews |  |  |  |  |  |  | 1055 | 1128 | 1204 | 1271 | 1418 | 1593 |
| Average Yelp Rating |  |  |  |  |  |  | 3.6 | 3.6 | 3.6 | 3.7 | 3.7 | 3.8 |
| Average Nr of Yelp Reviews |  |  |  |  |  |  | 54.8 | 69.1 | 74.3 | 80 | 95.5 | 106.5 |
| Nr. Rest. with OT Rating |  |  |  |  |  |  | 202 | 256 | 295 | 354 | 418 | 478 |
| Average OT Rating |  |  |  |  |  |  | 3.9 | 3.9 | 4 | 4 | 4 | 4.1 |
| Average Nr of OT Reviews |  |  |  |  |  |  | 182 | 189.4 | 198.4 | 171.5 | 161 | 115.5 |

Notes: Each observation corresponds to a restaurant listed in the Zagat guide in year Y. Cost, Food Rating, Décor Rating, and Service Rating are obtained from the Zagat guide. OT Participation is the number of restaurants in our sample participating in OT in year t . In Zagat at Time $t$ is the number of restaurants listed in Zagat in year t , and In Zagat at Time $t$ and $t-1$ is the number of restaurants that were listed in both year t and year $\mathrm{t}-1$. Matched to DOHMH is the number of restaurants we were able to match with inspections information from NYC's DOHMH. Exits is the number of restaurants that were last inspected by the DOHMH in year t or before. Nr. Rest. with Yelp/OT Reviews is the number of restaurants that have at least one review posted in Yelp/OT, Average Yelp/OT Rating is the average among all restaurants of their average Yelp/OT rating, and Average Nr. of Yelp/OT Reviews corresponds to the average number of reviews received by restaurants (conditional on receiving at least one review over the study period).

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 archive, we compiled a list of all restaurants that participated in OT between February 2002 and November 2014.

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 conducted over the course of a year that asks respondents to rate their dining experience at restaurants they visit. Each survey is composed of responses by about 45,000 surveyors who eat out $\sim 3$ times per week. ${ }^{9}$ 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 all NYC Zagat printed guides published between 2005 and 2016. We used optical character recognition (OCR) software to create a dataset that contains: restaurant name, address, cuisine, Zagat ratings (for food, décor, and service), and price. The values extracted by the OCR software were manually checked to ensure accuracy. ${ }^{10}$

## A. Descriptive Statistics

Table 1 provides an overview of the construction and coverage of our sample. Our analysis is based on restaurants listed in Zagat, for which we can obtain information on prices. Note that as information published in the Zagat guide for year $n$ must be based on surveys conducted in year $n-1$, we consider the prices published on each guide as corresponding to the year prior to their publication. Each year, the Zagat guide includes $\sim 2,000$ restaurants. On average, the attrition rate

[^3]between consecutive guides is $17.4 \%$. In the years we can infer exits from DOHMH inspections, we observe that, on average, $43.3 \%$ of restaurants no longer listed had failed. In the 12 years we analyze, 5,284 restaurants were included in the Zagat guides. While the DOHMH should inspect all restaurants in the city, we are only able to match $85 \%$ of restaurants (in years for which we have inspections information). This is not surprising, as the food establishments inspection program has been criticized for not inspecting all establishments. ${ }^{11}$ We only consider OpenTable and Yelp reviews starting in 2010, as before then only few reviews per year were posted.

OpenTable adoption increased significantly during the period we study. OT participation among restaurants listed in Zagat increased from 11\% in 2004 to $42 \%$ in 2014. Zagat lists all types of establishments, from hot dog stands that have little use for a reservation platform, to fine dining restaurants. Thus, in Figure 1 we divide restaurants by price quartiles to show adoption rates over time. Restaurant prices in the top $25 \%$ in 2014 ranged between $\$ 54$ and $\$ 585$ dollars. Restaurant prices in the $25 \%$ to $75 \%$ quartiles ranged between $\$ 29$ and $\$ 53$. Prices in the bottom $25 \%$ ranged between $\$ 6$ and $\$ 28$. Dividing the sample this way makes it evident that OT reaches a remarkable adoption rate among establishments likely to accept reservations. In 2011, $\sim 70 \%$ of top priced restaurants participated in the platform, and $\sim 50 \%$ of mid-priced restaurants. From 2011 the adoption rate remains nearly constant. Adoption by restaurants with prices in the lower quartile remains rare throughout the period studied - which is to be expected, as they may not benefit significantly from the platform (their per-guest margins may be too low to justify OT's fee, or they may not offer reservations). By 2013, use by diners was also high, with $56 \%$ of Zagat respondents stating that they typically make reservations online

[^4](Zagat 2013, p. 5). While towards the end of our analysis OT started facing competition, during the time we focus on none of them achieved significant success. In 2013 OpenTable was a near monopoly. It listed 29,000 restaurants whereas its closest competitor had barely 1,000. ${ }^{12}$


Figure 1: Fraction of Restaurants Listed in Zagat That Participate in OT over Time, by Price Quartiles.
Notes: Created by the authors based on all restaurants listed in the Zagat guides for years 2005-2014 and the list of restaurants listed in OpenTable during the respective year based on snapshots retrieved from the Internet Wayback Machine (www.archive.org). Price quartiles are determined based on the price listed in the Zagat guide for each year.

It is interesting to observe how OT adoption in NYC evolved over time geographically. Figure 2 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 participating in OT that did not participate in it on the previous period. These are, to a great extent, concentrated around restaurants that have already adopted. A natural explanation is that OT grew around places with a high concentration of restaurants and diners. However, attributing this pattern solely to the spatial distribution of restaurants and diners is probably misguided, as both restaurants and diners are widely distributed across NYC. We expect proximity to competitors that

12 See https://www.forbes.com/sites/jjcolao/2013/11/06/despite-a-near-monopoly-in-online-reservations-opentable-is-finally-innovating.
participate in the platform to influence both adoption and outcomes experienced by restaurants. While our primary focus is on studying the impact of OT participation on prices and survival, we do explore in our empirical analysis how the proximity to other restaurants that also participate in OT influences these outcomes.


Notes: Created by the authors using QGIS based on restaurants listed in the Zagat guides in the respective years and participating in OpenTable according to historical snapshots retrieved from the Internet Wayback Machine. In each panel, blue dots represent restaurants that were not participating in OT in the previous panel. Coordinates for each restaurant were determined using the address listed in Zagat and Google's geolocation API. Geographical divisions in the map represent NYC's 59 community districts and are based on a shapefile from NYC OpenData.

## IV. The Impact of OpenTable Adoption on Prices

We study whether the costs associated with the adoption of OT are passed down to customers through price using different strategies. A challenge germane to our analysis is that the decision to join OpenTable is endogenous and likely correlated with our dependent variables. 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 venues should be more likely to command higher prices and have better survival chances. We deal with endogeneity concerns with a multipronged strategy. We first rely on the increasing adoption of OT over time to implement a difference-in-differences approach. Note that over the period we study adoption reaches over $70 \%$ for restaurants in the top price quartile, and over $50 \%$ for restaurants in the $25 \%-75 \%$ price quartiles. The second strategy relies on the fact that the fees restaurants face do not depend on their adoption decision, but instead on how diners choose to complete reservations. Thus, we estimate the effect of OT relying not on adoption, but instead on a proxy of the reliance of each restaurant's customers on OT to make reservations. We build this proxy from information on the number of online reviews posted on different platforms. Additionally, we conduct a series of robustness tests to check the consistency and interpretation of our results.

## A. Difference-in-Differences Analysis

We first take advantage of the 12 years of panel data we compiled on restaurant prices and OT adoption to implement a difference-in-differences analysis. This period covers the platform almost since its inception and until it became dominant. In our estimations, we use regressions of the form:

$$
X_{i, t}=R_{i}+B_{t}+g * Z_{i, t}+\sigma * O T_{i, t}+e_{i, t}
$$

In this regression, $R_{i}$ is a vector of restaurant fixed effects. $B_{t}$ is a vector of time fixed effects. $Z_{i, t}$ is a vector of restaurant's $i$ characteristics at time $t$, which are obtained from the Zagat guide and include lagged price (i.e. price at time $t-$ 2), lagged price squared and ratings for food, décor, and service. ${ }^{13} O T_{i, t}$ is a dummy equal to 1 if restaurant $i$ participated in OT during period $t$, and zero otherwise. ${ }^{14}$ Finally, $e_{i, t}$ is the error term. We use robust standard errors clustered at the restaurant level. In this equation, $\sigma$ corresponds to the difference-in-differences estimator of OpenTable's effect on restaurants' price $X$.

Self-selection is an obvious concern in this analysis. Our dataset, however, is unusual in that it covers a period where OT adoption increased by a factor of $\sim 3.5 \mathrm{x}$ to cover over $40 \%$ of the entire sample, and more than $70 \%$ of restaurants in the top price quartile. Such broad coverage implies that most restaurants that are likely to require/offer reservations end up adopting the platform, which makes selfselection less of a concern. Additionally, as we use restaurant fixed effects, our identification is going to be driven by within restaurant price differences after adopting OT.

We analyze price differences over periods of 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. ${ }^{15}$ Table 2 presents four models based on the difference-in-differences framework. Model P1 only includes restaurant characteristics covariates, firm fixed effects, and the OT participation dummy. The coefficient of the OT dummy corresponds to the difference-in-differences estimator, and it is positive - although imprecisely measured, being only

[^5]statistically significant at the $10 \%$ level. The coefficient indicates that OT participation is associated with a price premium of $\$ 0.33$.

Table 2: The Effect of OT Participation on Prices

|  | P1 | P2 | P3 |
| :---: | :---: | :---: | :---: |
| OT | $0.332$ |  | -0.071 |
|  | (0.200) |  | $(0.250)$ |
| OT x Before 2011 |  | -0.244 |  |
|  |  | (0.272) |  |
| OT x From 2011 |  | 0.759 |  |
|  |  | (0.198) |  |
| High Adoption One Mile Same Cuisine |  |  | -0.074 |
|  |  |  | (0.172) |
| OT x High Adoption One Mile Same Cuisine |  |  | 1.159 |
|  |  |  | $(0.331)$ |
| Lagged Price | 0.383 | 0.378 | 0.378 |
|  | $(0.119)$ | $(0.118)$ | $(0.118)$ |
| Lagged Price Squared/1000 | 0.170 | 0.174 | 0.174 |
|  | (0.103) | (0.102) | (0.102) |
| Service Rating | -0.002 | 0.001 | -0.000 |
|  | (0.022) | (0.021) | (0.021) |
| Food Rating | 0.001 | 0.001 | 0.000 |
|  | (0.011) | (0.011) | (0.011) |
| Décor Rating | 0.062 | 0.067 | 0.066 |
|  | (0.031) | (0.032) | (0.031) |
| Constant | 22.832 | 22.942 | 22.991 |
|  | (4.134) | (4.128) | (4.106) |
| Restaurant Fixed Effects | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Observations | 15,058 | 15,058 | 15,058 |
| R-squared | 0.984 | 0.984 | 0.984 |

Notes: Dependent variable is price at time $t$. Robust standard errors clustered at the restaurant level. OT is equal to 1 if restaurant participates in OT at time t and 0 otherwise. Before/From 2011 is a dummy equal to 1 for observations Before/From 2011 and 0 otherwise. High Adoption One Mile Same Cuisine is equal to 1 if over half of the restaurants located within a one-mile radius and that serve food in the same cuisine participate in OT at time $t$ and 0 otherwise. Lagged Price and Lagged Price Squared over 1000 correspond to prices at $t-2$ according to the Zagat guide. Service, Food, and Décor Ratings correspond to Zagat Ratings (0-30 points) at time $t$.

A key motivation of our study is to determine how the effect of the platform changes as the platform becomes dominant. According to our model, the effect of adoption on prices depends on the fraction of buyers who use 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 different levels of adoption over time. As shown in Figure 1, OT adoption peaks around 2011 and remains stable thereafter. Thus, in model P2 we estimate the OT coefficient separately for observations up to 2011, and for observations after 2011. The coefficient estimate for OT before 2011 is not statistically significant, while the OT coefficient after 2011 is positive and statistically significant. This implies OT adoption is associated with a price increase of $\mathrm{U} \$ 0.76$ once the platform is being used by most restaurants. We next test how the OT effect on prices changes with increasing adoption at competing restaurants. In model P3 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, ${ }^{16}$ participate in OT, and zero otherwise (High Adoption One Mile Same Cuisine). ${ }^{17}$ We introduce this variable by itself and interacted with OT. The coefficient estimate of the interaction is positive and statistically significant, and it is higher than the OT coefficient obtained in model M2. This implies that restaurants that use OT, and for whom more than half of their direct competitors also participate in OT (as defined by cuisine type and geographical location), raise their prices by $\$ 1.16$ per guest.

[^6]
## B. Estimating OT's Effect on Prices Through Review Counts

Section II's model includes a parameter to account for the influence of users' awareness about the platform on the outcomes experienced by sellers. Sellers' adoption of the platform by itself is not what drives the effect on price. Instead, the impact depends on how many consumers decide to use the platform.

As the sellers' decision to adopt the platform is endogenous, for this analysis we estimate the effect of OT by using a proxy of how frequently diners use OT to make reservations. We include in the regression 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). The rationale is that if a large share of restaurant A's clients uses OT to book, we should see more reviews being posted for restaurant A in OT's review system compared to reviews posted in other sites. Additionally, we use the number of reviews posted in Yelp as a proxy for demand. We do so to control for an alternative explanation: the price increase we observe may be due to an increase in the demand the restaurant is facing, rather than being driven by participation and the fees charged by OT.

We attempt to collect all reviews posted in OT and Yelp for all restaurants in our dataset. However, this information is not always available. 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, and its average rating, are 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. The correlation between our estimated review count (based on the figures reported in OT's city listing) and the actual number of reviews we computed by scraping all reviews (for the restaurants for which we could obtain this information) is 0.96 , which makes us confident our approximation is accurate. We obtain approximate 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 extract 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 relative popularity of Yelp and OT fluctuates throughout the sample. In the first years, there were 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 ratio of OT/Yelp reviews as:

$$
\begin{aligned}
& {\text { Ratio } O T / Y_{\text {Yelp }}^{\text {iy }}} \\
& =\frac{1+\text { Normalized } \# \text { of OT Reviews for Restaurant } i \text { in year } y}{1+\text { Normalized \# of Yelp Reviews for Restaurant } i \text { in year } y}
\end{aligned}
$$

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. ${ }^{18}$

Table 3: Estimating the Effect of OT on Price Through Reviews Counts

|  | P4 | P5 | P6 |
| :---: | :---: | :---: | :---: |
| OT | 0.719 | 0.579 | 0.566 |
|  | (0.370) | (0.357) | (0.344) |
| Ratio OT/Yelp |  | 1.313 |  |
|  |  | (0.408) |  |
| Ratio OT/Yelp Quartile 1 |  |  | -0.454 |
|  |  |  | (0.319) |
| Ratio OT/Yelp Quartile 4 |  |  | 0.648 |
|  |  |  | (0.376) |
| \# Yelp Reviews |  | 0.167 | 0.117 |
|  |  | (0.135) | (0.143) |
| Lagged Price | 0.167 | 0.169 | 0.169 |
|  | (0.135) | (0.136) | (0.136) |
| Lagged Price Squared/1000 |  | 0.068 | 0.069 |
|  | (0.310) | (0.311) | (0.314) |
| Service Rating | -0.021 | -0.019 | -0.020 |
|  | (0.030) | (0.031) | (0.030) |
| Food Rating | 0.009 | 0.008 | 0.009 |
|  | (0.014) | (0.014) | (0.014) |
| Décor Rating | 0.044 | 0.048 | 0.046 |
|  | (0.045) | (0.045) | (0.043) |
| Constant | 36.095 | 34.771 | 39.133 |
|  | (5.673) | (5.809) | (5.869) |
| Year Fixed Effects | Yes | Yes | Yes |
| Restaurant Fixed Effects | Yes | Yes | Yes |
| Observations | 6,955 | 6,955 | 6,955 |
| R -squared | 0.987 | 0.987 | 0.987 |

Notes: Dependent variable is price at time $t$. Robust standard errors clustered at the restaurant level. OT is equal to 1 if restaurant participates in OT at time $t$ and 0 otherwise. These models only include observations starting in 2010, as we don't have information on reviews for earlier years. P4 replicates model P1 in this subsample. Ratio OT/Yelp corresponds to the ratio between $1+$ the normalized number of reviews received by the restaurant in OT over $1+$ the normalized number of reviews received by the restaurant in Yelp. Ratio OT/Yelp Quartile 1 (4) is equal to 1 for restaurants whose ratio OT/Yelp is in the lower (higher) quartile and 0 otherwise. Lagged Price and Lagged Price Squared/1000 correspond to prices at t-2 according to the Zagat guide. Service, Food, and Décor Ratings correspond to Zagat Ratings ( $0-30$ points) at time $t$.

[^7]In model P4 in table 3, we replicate model P1 using the subsample of restaurants for which we can obtain OT (approximated) and Yelp (actual) reviews, to verify that our baseline results are equivalent in this subsample. Note that all observations before 2010 were dropped, which explains why the OT coefficient we obtain is close to the "OT x From 2011" coefficient in model P2. In model P5 we introduce two additional variables: the Ratio OT/Yelp, and the normalized number of Yelp reviews. The coefficient of the Ratio OT/Yelp is positive and statistically significant. Moreover, the magnitude of the OT coefficient diminishes and is no longer statistically. ${ }^{19}$ A drawback of this specification is that our normalized ratio of OT vs. Yelp reviews variable does not have a straightforward economic interpretation. Thus, in model P6 we repeat the analysis, but instead of using the ratio variables as a continuous variable, we create two dummy variables: one that is equal to 1 for restaurants for which the Ratio OT/Yelp variable is in the bottom quartile (Ratio OT/Yelp Quartile 1), and one that is equal to 1 for restaurants for which the Ratio OT/Yelp variable is in the top quartile (Ratio OT/Yelp Quartile 4). This makes the interpretation of the coefficients straightforward. For restaurants in the bottom quartile of the Ratio OT/Yelp variable, the effect of OT participation is negligible at 0.11 dollars (Std.Err. 0.42). ${ }^{20}$ The effect for restaurants in the top quartile is 1.21 dollars (Std.Err. 0.53), while the effect for other restaurants that participate in OT is 0.57 (Std.Err. 0.34). These results are consistent with the estimates presented in the previous subsection and reaffirm the prediction of our model. Restaurants that seemingly get most of their clients through OT raise their prices in amounts very similar to the fee charged by OT, while restaurants that participate in OT but do not seem to get many clients from the platform don't raise their prices.

20 This corresponds to the lineal combinations of the OT and Ratio OT/Yelp Quartile 1 coefficients.

## C. Robustness Analysis and Alternative Explanations

To test the robustness of our analysis, we first implement a falsification test to check whether the price increase we observe happens after OpenTable is adopted and not leading to OpenTable adoption. It could be the case that restaurants that are experiencing increased demand both raise their prices and adopt OT to manage their reservations. For the falsification test we lead the OT coefficient by 1 year to estimate if there is a price increase a year ahead of OT adoption. As in most cases we have multiple observations after OT is adopted, in this model we exclude all observations 1 year after OT is adopted (and only include observations up to 2013 due to the lead). In model R1 in table 4, we first repeat our base analysis eliminating all observations for a period after OT is adopted to verify that we obtain results equivalent to our prior models in the subsample we use for this analysis. In model R2 we replace the OT variable with the Lead OT variable. The Lead OT coefficient estimate is not statistically significant and close to zero, which suggests the price effect we observe happens only after OT is adopted and not leading to its adoption.

While our analysis suggested there exists an association between OT adoption and an increase in prices, there are at least three different mechanisms that could be behind this price increase. Our preferred explanation is that the price increase is driven by an increase in costs that get passed down through price to consumers, as our model predicts. However, price increases may also be driven by increases in (actual or perceived) quality, which should increase consumers' willingness to pay. While OT should not directly increase quality, it could indirectly contribute to perceived quality by reducing search cost and leading to a better match between consumers' preferences and restaurants' offerings. It could also be the case that along with adopting OT, restaurants implement other improvements related to quality. To study whether OT adoption is related to changes in quality, we repeat our difference-in-differences specifications using restaurant rating instead of cost
as the dependent variable. Models R2-R4 in table 5 follow the same specification as models P1-P3 but using Zagat food rating as the dependent variable. In none of the models does OT have a statistically significant effect on restaurant's ratings.

| OT | R1 | R2 |
| :---: | :---: | :---: |
|  | $0.378$ |  |
|  | (0.225) |  |
| Lead OT |  | 0.105 |
|  |  | $(0.170)$ |
| Lagged Price | 0.238 | 0.23 |
|  | (0.122) | (0.130) |
| Lagged Price Squared/1000 | 0.349 | 0.357 |
|  | (0.124) | (0.132) |
| Service Rating | 0.068 | 0.073 |
|  | $(0.044)$ | $(0.054)$ |
| Food Rating | 0.005 | 0.007 |
|  | (0.011) | (0.011) |
| Décor Rating | 0.058 | 0.054 |
|  | (0.047) | (0.047) |
| Time Period Fixed Effects | Yes | Yes |
| Restaurant Fixed Effects | Yes | Yes |
| Constant | 22.706 | 22.511 |
|  | (4.575) | (4.892) |
| Observations | 8,612 | 8,227 |
| R -squared | 0.990 | 0.990 |
| Notes: Dependent variable is price at time t. Robust standard errors clustered at the restaurant level. For this analysis, for each restaurant we drop all observations 1 year after OT is adopted (and only consider observations up to 2013 to be able to lead variables). OT is equal to 1 if restaurant participates in OT at time $t$ and 0 otherwise. Model R1 replicates model P1 for the subsample used in this analysis. Lead OT is equal to 1 if restaurants will participate in OT at time $t+1$ and 0 otherwise. Lagged Price and Lagged Price Squared/ 1000 correspond to prices at t-2 according to the Zagat guide. Service, Food, and Décor Ratings correspond to Zagat Ratings ( $0-30$ points) at time t . |  |  |


|  | R3 | R4 | R5 |
| :---: | :---: | :---: | :---: |
| OT | 0.071 |  | 0.017 |
|  | (0.123) |  | (0.123) |
| OT x Before 2011 |  | 0.123 |  |
|  |  | (0.146) |  |
| OT x From 2011 |  | 0.032 |  |
|  |  | $(0.150)$ |  |
| High Adoption One Mile Same Cuisine |  |  | -0.100 |
|  |  |  | (0.116) |
| OT x High Adoption One Mile Same Cuisine |  |  | 0.181 |
|  |  |  | (0.154) |
| Lagged Food Rating | -0.065 | -0.066 | -0.065 |
|  | $(0.041)$ | (0.041) | (0.041) |
| Lagged Food Rating Squared/1000 | -0.717 | -0.712 | -0.724 |
|  | (0.628) | (0.628) | (0.629) |
| Price | -0.001 | -0.001 | -0.002 |
|  | (0.005) | (0.005) | (0.005) |
| Service Rating | 0.087 | 0.087 | 0.087 |
|  | (0.025) | (0.025) | (0.025) |
| Décor Rating | 0.164 | 0.163 | 0.164 |
|  | (0.074) | (0.074) | (0.074) |
| Constant | 23.03 | 23.00 | 23.03 |
|  | (0.489) | (0.489) | (0.491) |
| Restaurant Fixed Effects | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Observations | 15,062 | 15,062 | 15,062 |
| R-squared | 0.554 | 0.554 | 0.554 |

Notes: Robust standard errors clustered at the restaurant level. This table replicates model P1-P3 using Food Rating at time $t$ as DV instead of Price. OT is equal to 1 if restaurant participates in OT at time $t$ and 0 otherwise. Before/From 2011 is a dummy equal to 1 for observations Before/From 2011 and 0 otherwise. High Adoption One Mile Same Cuisine is equal to 1 if over half of the restaurants located within a one mile radius and that serve food in the same cuisine participate in OT at time $t$ and 0 otherwise. Lagged Food Rating and Food Rating Squared correspond to Food Ratings at t-2 according to the Zagat guide. Price, Food, and Décor Ratings correspond to average price and ratings as reported in the Zagat guide at time $t$.

Lastly, the price increase could be driven by an increase in demand. If adopting the reservation platform leads restaurants to have excess demand, this could allow them to raise prices. While we do not have an establishment-level measurement of demand, it should be the case that if prices are increased due to
excess demand there should be a positive effect on profits. In the next section we study the effect of OT on survival as a proxy for profits.

## V. The Impact of OpenTable Adoption on Restaurant Survival

The model presented in section I predicts that OT participation will not translate into higher profits for restaurants. While the platform may enable them to poach some customers from competitors, if their competitors also join the platform this advantage will disappear. Examining the relationship between OT participation and profits may also provide support to the cost pass-through explanation of the price increase we observe in section IV. If the price increase we observe does not translate into higher profits, it must correspond to cost pass-through. Unfortunately, we cannot get information on profits. We focus, instead, on the relationship between OT adoption and survival, as restaurants with negative profits should exit in the long term.

As explained in Section III, we can only obtain information on restaurants' inspections between July 2007 and July 2017. We thus 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 $\mathrm{Y}+1$ (or any year thereafter). Restaurants that were last inspected in 2016 or after are considered right censored.

We seek to determine whether participating in OT has a positive effect on increasing a restaurant's likelihood of survival. As in the price analysis, OT adoption is dependent on other covariates that are also likely to influence survival. To get a sense of how different variables are correlated with survival, Figure 3 shows the Kaplan-Meier Survival Estimates for restaurants by OT participation, and by price quartile. Figure 3.1 shows that restaurants that participate in OT
actually exit at a higher rate than restaurants that do not participate in OT. Figure 3.2 suggests that this may be driven by the fact that the most expensive restaurants (price quartile 4) have lower survival rates than other restaurants and that (as we showed in figure 1) these restaurants have the highest participation rate in OT.


Notes: Observations include all restaurants listed in the Zagat guide between 2008 and 2015 and that were inspected at least once by the NYC DOHMH between July 2007 and July 2017. Restaurants are assumed to exit in year Y if their last recorded inspection was in that year. Restaurants last inspected in 2016 are considered right censored.

The survival functions shown in Figure 3 show a complex relationship between price, OT adoption, and survival. To untangle this relationship, we use Coxproportional hazard models, shown in table 6 . 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 venues. For the establishments that are no longer included in the guide, we do not have updated information on prices and ratings. We thus include in the analysis only restaurants that are continuously covered in Zagat until they exit, or up to the last year of our survival analysis. We also repeat the analysis using all restaurants and inputting the missing information for restaurants that are no longer listed from the last data point we have 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 results obtained with this method (available from authors upon request) are similar.

In the 8 years of analysis, 989 restaurants were continuously listed in Zagat and inspected by NYC's DOHMH and 472 (48\%) of them exit at some point over the analysis period. In the first model shown in Table 7 (S1) we introduce the OT dummy variable, which is equal to 1 if the restaurant was participating in OT in the year of analysis and zero otherwise, along with controls for price and ratings (food, décor, and service), and fixed effects for neighborhood (community district), and cuisine. Restaurant fixed effects cannot be included in this specification. ${ }^{21}$ The only statistically significant coefficient is the one associated with food rating. This implies that an additional point of food rating is associated with an $8 \%$ decrease in failure probability. The coefficient corresponding to OT participation is not statistically significant.

In our motivation model, OT participation is not expected to have any effect on profits in equilibrium (i.e., under full adoption). However, the model suggests that if partial adoption were to happen and 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 do not find a statistically significant effect in either of these models.


Notes: Table reports coefficient estimates, and robust standard errors clustered at the restaurant level in parentheses. Analysis only considers restaurants continuously covered in Zagat until they exit, or up to the last year of our survival analysis (right censored). OT is equal to 1 if restaurant participates in OT at time $t$ and 0 otherwise. Before/From 2011 is a dummy equal to 1 for observations Before/From 2011 and 0 otherwise. High Adoption One Mile Same Cuisine is equal to 1 if over half of the restaurants located within a one-mile radius and that serve food in the same cuisine participate in OT at time $t$ and 0 otherwise. Price and Price squared are based on the average price reported in the Zagat guide at time t. Service, Food, and Décor Ratings correspond to Zagat Ratings (0-30 points) at time $t$. The community district fixed effects are based on the location of the restaurant (there are 59 community districts in NYC).

## V. Discussion and Implications

Across many legacy industries, intermediaries are interjecting themselves in previously direct firm-to-consumer transactions, offering a complementary way of completing activities (such as booking restaurants or consuming news) through
online platforms. While these intermediaries have the potential to increase efficiency through economies of digitization, the extent of gains they can generate by intermediating a pre-existing market relationship is unclear. We contribute to this debate by providing novel evidence of the impact of increasing intermediation on prices and survival in the context of a highly competitive industry.

We motivate our empirical analysis with a simple model that shows how an intermediary platform may induce a prisoner's dilemma that leads sellers to adopt it, even if they cannot expect gains from participating in the platform. The main insight of this model is simple. If the intermediary is not changing the market in a way that would attract additional consumers to the industry, and instead is just reshuffling consumers between adopters and non-adopters, sellers will not get benefits from adoption. They will, nevertheless, adopt - as otherwise they would lose consumers to others that choose to adopt. Moreover, the ability of the platform to extract the benefits it creates grows with its popularity, until the platform is able to extract all the surplus it generates. This type of intermediation appears common in legacy industries that are increasingly becoming mediated by online platforms, but that otherwise continue to operate unchanged.

We examine the effect of an intermediary becoming dominant in a legacy market by studying OpenTable adoption in the restaurant industry in New York City. This is an expedient setting for our analysis: OpenTable only changes the way reservations are made; we can observe the platform almost from its inception until it becomes dominant; and the restaurant industry is highly competitive and operates with narrow margins. We implement multiple identification strategies and consistently find that the adoption of the platform is associated with a price increase similar to the costs of the platform. We repeat the analysis to try to establish whether adoption has any effect on restaurant survival (a proxy for profits), but do not find a consistent impact of adoption on survival.

The high degree of cost pass-through and the lack of evidence of any statistically significant effect on survival rates suggest that the platform is not helping restaurants gain efficiency or increase their profits, but instead is acting as an additional convenience to consumers that comes at a cost for restaurants, which in turn pass it down to consumers through price. It also highlights how what seems like a small fee may amount to a substantial cost in competitive industries that operate with narrow margins. While our empirical analysis is centered around restaurants in NYC, our model and results apply to many long-established industries that are now increasingly getting intermediated by online platforms.

## REFERENCES

Allegretto, Sylvia, and Michael Reich. 2018. "Are Local Minimum Wages Absorbed by Price Increases? Estimates from Internet-Based Restaurant Menus." ILR Review 71 (1): 35-63.

Anderson, Chris. 2006. The Long Tail: Why the Future of Business Is Selling Less of More. Hachette Books.

Armstrong, Mark. 2006. "Competition in Two-Sided Markets." The RAND Journal of Economics 37 (3): 668-91.

Brown, Jeffrey R., and Austan Goolsbee. 2002. "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry." Journal of Political Economy 110 (3): 481-507.

Brynjolfsson, Erik, Yu (Jeffrey) Hu, and Duncan Simester. 2011. "Goodbye Pareto Principle, Hello Long Tail: The Effect of Search Costs on the Concentration of Product Sales." Management Science 57 (8): 1373-86.

Brynjolfsson, Erik, and Michael D. Smith. 2000. "Frictionless Commerce? A Comparison of Internet and Conventional Retailers." Management Science 46 (4): 563-85.

Bulow, Jeremy I., and Paul Pfleiderer. 1983. "A Note on the Effect of Cost Changes on Prices." Journal of Political Economy 91 (1): 182-85.

Cawley, John, Chelsea Crain, David Frisvold, and David Jones. 2018. "The PassThrough of the Largest Tax on Sugar-Sweetened Beverages: The Case of Boulder, Colorado." w25050. National Bureau of Economic Research.

City of New York - Office of the Comptroller. 2009. "Audit Report on the Department of Health and Mental Hygiene Oversight of the Correction of Health Code Violations at Restaurants."

City of New York - Office of the Comptroller. 2015. "Audit Report on the New York City Department of Health and Mental Hygiene's Follow-up on Health

## Code Violations at Restaurants."

Edelman, Benjamin, and Michael Luca. 2014. "Digital Discrimination: The Case of Airbnb.Com." Harvard Business School Working Paper Series.
Edelman, Benjamin, and Julian Wright. 2015. "Price Coherence and Excessive Intermediation." The Quarterly Journal of Economics 130 (3): 1283-1328.

Einav, Liran, Chiara Farronato, and Jonathan Levin. 2015. "Peer-to-Peer Markets." w21496. National Bureau of Economic Research.
Farronato, Chiara, and Andrey Fradkin. 2018. "The Welfare Effects of Peer Entry in the Accommodation Market: The Case of Airbnb." w24361. National Bureau of Economic Research.
Frankel, Alan S. 1998. "MONOPOLY AND COMPETITION IN THE SUPPLY AND EXCHANGE OF MONEY." Antitrust Law Journal 66 (2): 313-61. https://www.jstor.org/stable/40843401.
Goldfarb, Avi, and Catherine Tucker. 2019. "Digital Economics." Journal of Economic Literature 57 (1): 3-43.

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

Luca, Michael. 2016. "Reviews, Reputation, and Revenue: The Case of Yelp.Com." SSRN Scholarly Paper ID 1928601.
Morton, Fiona Scott, Florian Zettelmeyer, and Jorge Silva-Risso. 2001. "Internet
Car Retailing." The Journal of Industrial Economics 49 (4): 501-19.
Orlov, Eugene. 2011. "How Does the Internet Influence Price Dispersion? Evidence from the Airline Industry." The Journal of Industrial Economics 59 (1): 21-37.

Rochet, Jean-Charles, and Jean Tirole. 2006. "Two-Sided Markets: A Progress Report." The RAND Journal of Economics 37 (3): 645-67.

Seamans, Robert, and Feng Zhu. 2014. "Responses to Entry in Multi-Sided

Markets: The Impact of Craigslist on Local Newspapers." Management Science 60 (2): 476-93.

Spiegler, Ran. 2000. "Extracting Interaction-Created Surplus." Games and Economic Behavior 30 (1): 142-62.

Waldfogel, Joel, and Lu Chen. 2006. "Does Information Undermine Brand? Information Intermediary Use and Preference for Branded Web Retailers." The Journal of Industrial Economics 54 (4): 425-49.

Wright, Julian. 2012. "Why Payment Card Fees Are Biased against Retailers." The RAND Journal of Economics 43 (4): 761-80.

Yang, Huanxing. 2013. "Targeted Search and the Long Tail Effect." The RAND Journal of Economics 44 (4): 733-56.

Zagat. 2013. 2014 New York City Restaurants. Zagat Survey New York City Restaurants edition. New York, NY: ZAGAT.
Zervas, Georgios, Davide Proserpio, and John W. Byers. 2017. "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry." Journal of Marketing Research, January.


[^0]:    * Cheyre: Ann S. Bowers College of Computing and Information Science, Cornell University. Gates Hall 215, 107 Hoy Rd, Ithaca, NY 14850 (e-mail: cac555@cornell.edu). Acquisti: Heinz College, Carnegie Mellon University, 5000 Forbes Av, Pittsburgh, PA 15213 (e-mail: acquisti@andrew.cmu.edu). We are grateful to Lee Branstetter, Brian Kovak, Ben Edelman, Chris Forman, Martin Gaynor, and Lowell Taylor for comments and suggestions, as well as seminar participants at Arizona State University, Carnegie Mellon University, the Copenhagen Business School, Cornell University, The University of Arkansas, The University of Minnesota, Tilburg University, the 2018 Workshop of Information System and Economics, the 2018 International Conference on Information Systems, the 2021 Paris Conference on Digital Economics, and the 2021 Learning and Decision-Making with Strategic Feedback Workshop. We thank Ahmad Salah Ud Din and Raj Sachdev for excellent research assistance. This research was partly funded by Acquisti's grant G-2015-14111 from the Alfred P. Sloan Foundation.

[^1]:    1 Note that while we are considering the location to be exogenously determined, locating at the ends of the unit line is the optimal decision when location is determined endogenously in a Hotelling model with quadratic transportation costs. As relocation is costly, we think that this is a reasonable assumption if the sellers are operating in equilibrium before the intermediary is introduced.

[^2]:    6 https://www.forbes.com/sites/jjcolao/2013/11/06/despite-a-near-monopoly-in-online-reservations-opentable-is-finallyinnovating.

    7 We could not find a precise account of the date this feature was introduced. However, using the Internet Wayback Machine, we determine that it was first featured in OpenTable's website around April 2003.

    8 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 requested to be re-inspected to improve their preliminary grade.

[^3]:    9 Until 2014, each Zagat guide contained a page with details about the survey. For example, the 2014 guide reports 48,114 respondents who reportedly eat 4.9 meals out per week (Zagat 2013, p. 5).

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

[^4]:    11 In 2009, an audit to the food safety inspection program in NYC revealed that not all restaurants were being inspected annually (City of New York 2009). In 2015, another audit identified that the DOHMH experienced frequent delays in conducting follow-up inspections (City of New York 2015).

[^5]:    13 In Zagat, ratings are displayed in a $0-30$ continuous scale, and prices correspond to the average dollar amount that respondents reported spending in a meal.

    14 We have information on OT participation up to November 2014. When 2015 data is needed, we consider OT participation in 2015 remains constant from 2014. Repeating the analysis omitting 2015 yields comparable results. We consider a restaurant participated in OT in year i if it appeared in more than half of the snapshots we retrieved from the IWM for that year.

    15 We also perform the analysis using yearly price differences (for all models presented in this paper). Results are similar to those presented here.

[^6]:    16 In the Zagat guide, restaurants are categorized into over 100 types of cuisine. We map this classification into 13 broadly defined food categories in which group restaurants are likely to compete. The categories include: American, Italian, French, Japanese, Mexican, Asian, Latin American, European, Bakery/Cafes, Pubs/Bars, African/Australian, Middle Eastern, and Others.

    17 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.

[^7]:    18 Restaurants we cannot get OT reviews for (and that participated in OT at any time), or that we do not locate in Yelp, are excluded from the analysis.

