UNIVERSITY OF CALIFORNIA

Los Angeles

Shrouded Information and Strategic Transparency: Three Essays on Price Obfuscation

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Management

by

Elizabeth Bennett Stulting Chiles

2017

ABSTRACT OF THE DISSERTATION

Shrouded Information and Strategic Transparency:

Three Essays on Price Obfuscation

by

Elizabeth Bennett Stulting Chiles

Doctor of Philosophy in Management

University of California, Los Angeles, 2017

Professor Marvin B. Lieberman, Chair

Many firms engage in activities aimed at making prices less transparent – tactics that may be referred to collectively as *price obfuscation*. Existing theory does not explain the substantial heterogeneity that exists both within and across industries with respect to the prevalence of these practices. The essays herein thus seek to shed further light on this phenomenon. In particular, I address several interrelated questions: what incentives drive firms to obfuscate in the first place, what are the potential consequences (if any) of doing so, and how do these tradeoffs vary depending on firm characteristics and market conditions? Novel empirical results are drawn from U.S. hotel industry data in Chapters 1 and 2; in Chapter 3, I synthesize existing price obfuscation literature from a range of disciplines and provide several illustrative case studies. Taken together, these three essays build toward a more comprehensive theoretical framework for understanding why, in practice, some firms utilize obfuscation (and deceptive tactics more broadly) while others do not.

The dissertation of Elizabeth Bennett Stulting Chiles is approved.

John Asker

Ian Larkin

Mariko Sakakibara

Marvin B. Lieberman, Committee Chair

University of California, Los Angeles

2017

To Chris

Table of Contents

List of Figures

List of Tables

Acknowledgments

I am deeply grateful to my advisor, Marvin Lieberman, and to the additional members of my committee – John Asker, Ian Larkin, and Mariko Sakakibara – for their time and support. I also thank Fred Chen for his detailed feedback on Chapter 2 (and, more broadly, for his steady encouragement for many, many years). My kind colleague Cristian Ramírez and seminar participants at Wake Forest University, Columbia Business School, the Kenan-Flagler Business School at UNC Chapel Hill, and the Fuqua School of Business at Duke also provided thoughtful and constructive input towards this endeavor. Jen Fryzel at Expedia spent generous time answering questions relating to the data and the hotel industry. Finally, I am especially indebted to Jason Snyder, whose guidance in the early stages of my dissertation work was instrumental in shaping my research.

Vita

2017–present	**Assistant Professor of Management**, Columbia Business School *New York, NY*
2012–2017	**Doctoral Student in Strategy**, UCLA Anderson School of Management *Los Angeles, CA*
2015–2017	**Data Scientist**, Hazel Analytics *Los Angeles, CA*
2011–2012	**Commercial Strategies Analyst**, Wells Fargo Bank *Los Angeles, CA*
2010–2011	**Visitor & Volunteer Relations Manager**, McColl Center *Charlotte, NC*
2009–2010	**AmeriCorps Construction Crew Leader**, Habitat for Humanity *Charlotte, NC*
2007–2009	**Analyst**, Dean & Company Strategy Consultants *Washington, DC Area*
2007	**B.S.**, Mathematical Economics and Art History, *summa cum laude* Wake Forest University *Winston-Salem, NC*

WHAT *Is* PRICE OBFUSCATION?

Firms in many industries strategically exploit the cognitive limitations of consumers by making information about their products more difficult, confusing, or time-consuming to discern. Tactics that reduce price transparency are particularly common. Investment management companies shroud fees for mutual funds, 401(k) administration, and advisory services in fine print.[1] Insurance carriers and wireless providers utilize complex, multi-dimensional pricing structures[2] that often leave consumers surprised upon receipt of their final bill.[3] Retailers of consumer goods from mattresses to groceries commonly employ inconsistent descriptors and units of measurement across products, making price comparisons challenging.[4] And even the most seasoned of travelers may find the continuing proliferation of surcharges at hotels, airlines, and rental car companies confusing.[5]

A growing literature explores the various ways in which firms can (and do) obfuscate prices, and authors from various disciplines use a range of terminology to describe this phenomena. To avoid confusion, it is helpful to specify precisely what I mean by "price obfuscation" within the context of this dissertation. I propose the following definition: any tactic utilized by firms for the purpose of preventing consumers from becoming fully informed about market prices. This is somewhat similar to the way in which Akerlof and Shiller (2015) define informational "phishing" – the presentation of information in a way that is intentionally crafted to mislead. Importantly, like that of Akerlof and Shiller, my definition involves an *intent* to suppress (or confuse) information, underscoring the notion that while price obfuscation is not explicitly illegal in many cases, its utilization may fall into murky ethical territory.

---

[1]E.g., Housel, 2015

[2]In addition to being complex, it is also not uncommon for these menus to include strictly dominated options (Miravete, 2013; Handel, 2013; Grubb 2015).

[3]Prior to 2011 FCC regulations, one in six users experienced monthly "bill shock" over unexpected charges (Wyatt, 2011).

[4]E.g., Chioveanu and Zhou, 2013

[5]E.g., Sharkey, 2013; Sablich, 2017

At first blush, it seems that firms must have obvious incentives to engage in price obfuscation – if consumers can be fooled by these tactics, then why *not* partake? And, indeed, existing literature has focused largely on establishing the short-term financial benefits of obfuscation. Empirically, however, there is a great deal of heterogeneity, both within and across industries, with respect to the prevalence of these practices. How can we explain this heterogeneity? What market factors might foster more (or less) transparency? How does a firm's strategy and market position influence its incentives to exploit consumers' cognitive limitations? This dissertation aims to shed light on these questions, contributing not only to the literature on information disclosure, but also more broadly to the growing body of research on ethically questionable business practices.

CHAPTER 1

Resorting to Obfuscation: When do Firms Adopt Shrouded Pricing?

1.1 Introduction

Why does price obfuscation proliferate in some markets and not others? This paper seeks to shed light on the drivers of one form of obfuscation – shrouded surcharges[1] – with particular focus on the role that competitive pressure and strategic interactions play in shaping price transparency. Existing theories offer differing conclusions with respect to the effect that competition should have on firms' propensity to obfuscate prices, although on net the literature seems to suggest that firms will obfuscate more when competition is more intense. In formal price obfuscation models, the assumptions that facilitate this conclusion are often quite specific with regard to how consumers will behave when they are confused or uninformed. Shleifer (2004) offers some intuition that is more general and, perhaps, more relevant for this particular paper: when competition becomes more intense, firms become more willing to engage in ethically questionable practices that either lower costs or increase revenue. Within this framework, heightened competition results in more obfuscation, and obfuscation by one firm encourages other firms to follow suit.

Using data from the U.S. hotel industry, I seek to address three key questions. First, what is the empirical relationship between competitive intensity and price obfuscation? Specifically, I examine two forms of competition: intra-industry competition (measured by the number

[1] Throughout, I use the terms "obfuscation," "shrouded surcharges," and "hidden fees" interchangeably.

of other hotels in a given market) and substitute industry competition (measured by the number of vacation rental properties listed in a given market). Empirical findings support the prediction that competition drives obfuscation – an additional ten hotel competitors is associated with a one to two percentage point increase in a firm's propensity to adopt a "resort fee," i.e., a shrouded mandatory surcharge. Results echo findings from a growing number of researchers (e.g., Cai et al. (2005), Snyder (2010), Bennett et al. (2013), Mayzlin et al. (2014), and Luca and Zervas (2015)) who have found that firms, when faced with heightened competitive pressure, do not always attempt to cut costs or improve quality. Rather, they often attempt to compete along unproductive, ethically questionable dimensions – in this case, price transparency (or rather, lack thereof). Thus, while competition may certainly drive many positive outcomes, as Cai et al. (2005) observe, "the effects of competition critically depend on the instruments firms use in order to compete."

A second empirical question is: do strategic interactions between firms influence shrouding behavior among competitors in a given market? Here, I assess the extent to which a firm's decision to shroud (to adopt a resort fee) depends on competitors' shrouding decisions. To address endogeneity – shrouding decisions among a firm and its competitors may both be correlated with unobserved market-level factors – I employ an instrumental variables strategy. Specifically, I exploit the fact that for chain-affiliated hotels, there is within-chain correlation in resort fee utilization *across* markets. Consider two hotels in the Los Angeles market: a Hilton and a Best Western. The rate at which Hilton hotels in *other* markets adopt resort fees is correlated with Hilton's probability of adopting a resort fee in Los Angeles. But this should have no effect on the Los Angeles Best Western's propensity to shroud, except to the extent that chain-level norms shape Hilton's shrouding choices in the LA market. I thus instrument chain-affiliated competitors' shrouding decisions in market j with the chain's overall propensity to shroud in other markets $(-j)$. Empirical results indicate that shrouding decisions are strategic complements, in line with what theory would predict.

Finally, a third contribution of this paper is the sharp empirical distinction that I am able to draw between the conditions under which mandatory versus avoidable surcharges arise. (Here, specifically, I contrast resort fees, which are mandatory, with avoidable fees for wireless internet.) In Gabaix and Laibson's (2006) hugely influential model of shrouded add-ons, the authors point explicitly to optional add-ons in the hotel industry as examples of shrouded pricing, i.e., price obfuscation. While my empirical results here cannot offer definitive conclusions one way or the other, they cast doubt on this characterization. As a practical matter, I show that firms utilize mandatory and optional surcharges very differently. In particular, many of the factors that theory suggests should drive obfuscation are positively associated with resort fee prevalence but have zero or even negative correlation with the utilization of WiFi fees. While in many cases avoidable add-ons may, indeed, be a form of price obfuscation, in light of this evidence, it seems prudent to refrain from gratuitously categorizing *all* surcharges as obfuscation. In many instances, add-on pricing may simply be a classic case of price discrimination.

1.2 Motivation and Prior Literature

Existing work has yielded mixed conclusions with regard to the relationship between competition and obfuscation.[2] In Gabaix and Laibson (2006) – perhaps the most well-known model of shrouded pricing – key results are independent of the number of competitors in the market (in other words, competition doesn't exacerbate shrouding, but it doesn't eradicate it either). Instead, whether or not firms shroud depends on the portion of "myopic" buyers in the market. In line with this view, Miravete (2013) finds no empirical evidence that pricing in the U.S. cellular telephone industry became either any more or any less transparent as the industry transitioned from monopoly to duopoly. Similarly, Kalayci (2015) varies the number of sellers in an experimental setting and finds that the average level of price complexity selected is no different between treatments with two, three, and five sellers. Wenzel (2014) builds on Gabaix and Laibson's model, showing that a small adjustment in assumptions

[2] I focus my review of this literature primarily on those papers that address the incentives around transparency in *pricing*; for an excellent review of the literature on *quality* disclosure, see Dranove and Gin (2010).

around how consumers learn results in an outcome where shrouding actually becomes *less* prevalent as the number of competing firms increases.

In contrast, Spiegler (2006), Carlin (2009), and Chioveanu and Zhou (2013) present models in which firms' propensity to obfuscate is increasing in the number of competitors. All of these models center on obfuscation in the form of price *complexity* – frameworks where prices are multidimensional and potentially confusing for consumers. In Carlin and in Chioveanu and Zhou, some consumers act rationally while confused consumers make product selections at random. In Spiegler, cognitively limited buyers randomly select one price-quality dimension to evaluate and make (conditionally rational) product selections based solely on this one attribute (e.g., imagine a consumer who selects a bank based solely on ATM fees while ignoring fees for monthly maintenance, overdraft, etc.). In all three of these models, the assumption that some buyers ultimately randomize some element(s) of their selection process is critical to the result that obfuscation increases in the number of competitors. Yet the extent to which this assumption seems reasonable varies substantially depending on the empirical context. In particular, the relevance of this sort of model in the case of shrouded surcharges (as opposed to complex multi-pronged pricing schemes) is highly suspect. In the hotel industry, for example, consumers might be "confused" by shrouded surcharges in the sense that they may fail to notice them or systematically underestimate them when making comparisons between firms. But they almost certainly make decisions in the context of the hotel's (clearly observed) base price rather than completely at random. The conclusion, then, that obfuscation should increase with competition does not necessarily follow in this setting.

Alternatively, if we think of obfuscation not simply as a pricing strategy but more broadly as an ethically questionable practice (that firms would prefer to avoid), the expected role of competition becomes more clear-cut: obfuscation should increase with competitive pressure. Shleifer (2004) presents this thesis in an argument mirroring Becker's (1957) writings on discrimination.[3] The key underlying assumption here is that managers value ethical behavior,

[3]To be clear, Shleifer does not address price obfuscation specifically; his arguments are about ethically questionable practices more generally.

"but that such behavior is a normal good." So when industry profits fall (e.g., when competition becomes more intense), managers' demand for ethical behavior falls as well, "leading to the spread of censured practices." In other words, as profits become more difficult to capture, firms become more willing to engage in ethically questionable practices that either lower costs or increase revenues.

This basic intuition seems quite plausible in many settings, including the empirical setting for this paper: hotel industry managers claim to despise shrouded surcharges, yet argue that, ". . . we are hamstrung. In this race to the cheapest marketable price-tag, properties have no choice but to oblige. You would lose business to competitors if you didn't follow suit." (Mogelonsky, 2012) Several empirical papers provide evidence for the relevance of this perspective. Cai et al. (2005) find that firms in more competitive markets are more likely to engage in profit-hiding (i.e., tax evasion). In a study of the liver transplant industry, Snyder (2010) finds that transplant centers' propensity to manipulate the waiting list is higher in markets with multiple competitors. Bennett et al. (2013) study the vehicle emissions market and find that competition increases inspection leniency: "firm misconduct appears to increase with competitive pressure and the threat of losing customers to rival firms." Mayzlin et al. (2014) and Luca and Zervas (2015) both present evidence that firms (hotels and restaurants, respectively) in more competitive markets are more likely to receive fake negative reviews – ostensibly written by rival firms.

Applying Shleifer's framework, competitive pressure breeds obfuscation, and – importantly – one firm's obfuscation leads others to follow suit. This brings to mind similar insights from Ellison and Ellison (2009), who observe that as the Internet has made prices more competitive, firms have turned to obfuscation in an effort to frustrate consumers' ability to search and compare prices.[4] Moreover, they argue, if a firm opts to disclose a fully transparent price, it will be "buried" behind many misleadingly low(er) offers in search results. Thus, whenever one firm obfuscates, it is very difficult for others not to copy. Taken together, these insights

[4]The authors' primary focus in this paper is not to empirically demonstrate the link between competition and obfuscation (their key empirical result is that obfuscation can be wildly effective at raising markups). Still, their peripheral observations regarding competition and strategic interactions are quite relevant here.

motivate the two key hypotheses to be tested empirically in this paper:

Hypothesis 1 (H1): *As competitive density in a market increases, firms' propensity to obfuscate prices also increases.*

Hypothesis 2 (H2): *Shrouding decisions are strategic complements, i.e., a firm's propensity to obfuscate prices increases as a greater share of its competitors obfuscate.*

1.3 Empirical Context and Data

1.3.1 Shrouded Surcharges in the Hotel Industry

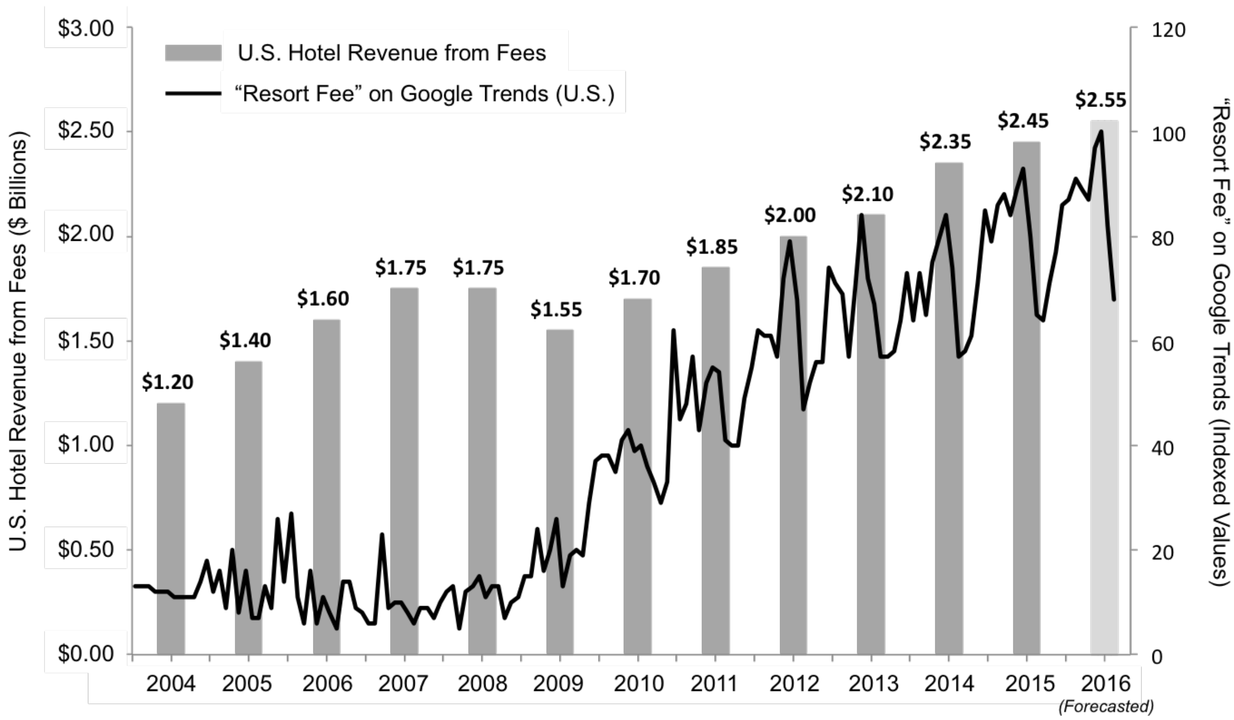
My empirical analysis focuses on the hotel industry, where shrouded surcharges are both relatively common and increasing in prevalence. As Figure 1.1 illustrates, total U.S. hotel revenue from fees (both mandatory surcharges and fees for avoidable add-on goods – e.g., wireless internet ("WiFi," hereafter), parking, late check-out, infant cribs, etc.) has doubled over the last decade or so, reaching $2.45 billion in 2015.[5] In this paper, I focus on two of the most commonly implemented surcharges: resort fees[6] (a type of mandatory surcharge) and WiFi fees. Unlike room rates, which often fluctuate daily, these surcharges are typically implemented as a flat dollar amount charged per night. Roughly 10-11% of hotels in my dataset utilize one or both of these shrouded charges at some point during the sample window.

Partitioning total price into a base price and a mandatory (shrouded) resort fee is attractive to hotels primarily because it allows them to advertise a misleadingly low room rate up front. This low rate is the price that is visible to consumers during search. The additional

[5]For context, overall revenue for the hotel industry was estimated at $176 billion in 2014 by the American Hotel & Lodging Association.

[6]Resort fees are also sometimes known by other names such as "convenience fees," "service fees," "amenity fees," "facilities fees," or "destination fees." Historically, these fees were charged only by genuine "resorts," and were justified to customers as necessary to maintain expansive pool, spa, and fitness facilities. Today, however, many hotels that are *not* resorts in any traditional sense have adopted these surcharges. Other mandatory surcharges include energy fees and cleaning fees; I focus only on resort fees in this paper, however, as they are by far the most common type of mandatory surcharge in the hotel setting.

Figure 1.1: Trends in U.S. Hotel Fees



Source for Revenue Data: Hanson (2016).
Note that revenue from fees includes both mandatory and avoidable surcharges.

fee, in contrast, is typically not disclosed until later in the booking process – often after the consumer has provided all necessary booking information, and even then, often only in fine print. Because payment is generally not due at the time of booking but rather at the time of *departure* from the hotel, many buyers may not notice resort fee surcharges when making their purchase decision. And even if buyers are aware of the fees at the time of booking, it is likely that many do not fully account for them until payment is actually due (as in Morwitz, Greenleaf, and Johnson (1998), where consumers fail to fully account for partitioned surcharges). News coverage and anecdotal evidence from traveler reviews suggest that consumers are often, indeed, both surprised and angry about resort fees upon the receipt of their final bill.[7]

[7]Accordingly, resort fees have come under fire from both consumer groups and policymakers. Most recently (in January 2017), the FTC issued a report concluding that resort fees are harmful to consumers. It remains unclear, however, whether or not resort fees will eventually be banned, either by the FTC or via legislative

A hotel's motivation for implementing WiFi fees is less clear-cut, since these charges are avoidable. As with resort fees, at least some travelers appear to be unaware of these added surcharges at the time of purchase (e.g., White, 2015) – so perhaps there is, indeed, an intent to mislead on the part of firms. If this is the case, then WiFi fees might arguably be classified as a form of "shrouded add-on pricing" as described by Gabaix and Laibson (2006). Another possibility, however, is that WiFi fees are simply a classic case of price discrimination. In Section 1.4, I contrast empirical results for resort fees with those for WiFi fees and discuss what these findings suggest with regard to which framework (shrouded pricing or price discrimination) seems most relevant for avoidable add-ons in this setting.

1.3.2 Data

I utilize data collected from several sources. Firm-level data (in all instances here, "firm" refers to an individual hotel property) was collected from Hotels.com, an Expedia subsidiary.[8] This data includes information on shrouded surcharges (resort fees and/or fees for WiFi) as well as a wealth of additional detail about the property: name (from which I can derive chain affiliation), assigned star category,[9] location, size (measured in number of rooms), price, and information on whether or not the hotel offers a wide range of amenities (e.g., pools, spa, fitness facilities, conference space, airport shuttle, etc.). For the empirical analyses presented here, I merge two cross-sectional snapshots of this data (collected in April 2015 and April 2017, respectively) to form a panel. All firm-level variables are allowed to vary over time, although there is very little change in many firm characteristics between the two periods in my sample (e.g., star categorization, number of rooms, and physical amenities tend to remain fixed – although even here there are a small number of firms that undergo changes.). There

action (Senator Claire McCaskill introduced a bill in February 2016 that would require hotels to advertise prices *inclusive* of any mandatory surcharges, but as of May 2017 it has not been brought to a vote).

[8]See Section 2.3 for general information on Expedia and the OTA channel.

[9]Star categories are assigned to properties by Expedia. Hotels may receive star categorizations between 1 and 5 in half-star increments which reflect the level of accommodations and services that the hotel offers. Stars can be thought of as a rough approximation for a firm's level of vertical differentiation.

is substantially more variation over time in price, in the services that hotels offer (e.g., fitness classes, concierge services, airport shuttle service, etc.), and in their utilization of shrouded surcharges. In addition, more than 2,000 hotels change chain affiliation during the sample period (either from independent to chain-affiliated, from chain-affiliated to independent, or from one chain to another).

The set of U.S. hotels listed on Hotels.com is quite comprehensive. As of April 2015, nearly 45,000 properties were listed on the site, reflecting approximately 85% coverage of the entire U.S. hotel market.[10] I assume that the set of hotels listed on Hotels.com is a reasonable proxy for the set of hotels in the overall U.S. market, and construct metrics for market structure accordingly. Specifically, I define "market" at the ZIP-5 level for all empirical analyses,[11] and define a hotel's competitors to be those firms located within its same ZIP-5 area. In total, my data includes 8,864 ZIP-5 markets.[12]

For all empirical results presented in this chapter, I focus on the set of 40,291 hotels that satisfy the following characteristics:

- *Present throughout the entire panel (i.e., firms that first list on Hotels.com after April 2015 or delist prior to April 2017 are excluded)*
- *Hotels.com record contains complete information for firm-level variables (e.g., if a hotel is missing a star category assignment on Hotels.com, it is excluded)*

Roughly 10% of the raw sample of hotels is discarded in this process. Note, however, that the number of competitors in the market (described above) is calculated *before* the data is trimmed – so while a firm without a star category assignment will not be one the 40,291 firms that make up the core sample, it *will* be included in the sense that competition metrics for its corresponding ZIP-5 will reflect its presence. Entry and exit over time are thus reflected in competition metrics as well.

---

[10] Per the American Hotel and Lodging Association, there were 53,000 hotels in the U.S. in 2015.

[11] All results presented are substantively unchanged if markets are defined in other ways (e.g., at the ZIP-3 level, at the MSA-level, as the area within a fixed radius of a given hotel). I discuss this more in Section 1.4.

[12] I also utilize fixed effects at the MSA-level in some specifications. My data spans 976 MSA-markets – implying 9 ZIP-5 areas per MSA on average.

In addition to intra-industry rivalry, the presence and growth of substitute industries may also contribute to competitive pressure. In the hotel setting, the growth of the vacation rental industry has exploded with the entry of online marketplaces. Airbnb is the most famous example, and its disruptive effect has been studied extensively (e.g., Zervas and Proserpio (2014) find that a 1% increase in Airbnb listings results a 0.05% decrease in quarterly hotel revenue). While Airbnb remains dominant (reporting roughly 3 million listings worldwide in November 2016[13]), TripAdvisor[14] has also – quietly – become a formidable player in this space, reaching 835,000 listings worldwide at year end 2016.[15] Both platforms have continued to grow rapidly over the last several years. For this study, I utilize data on vacation rental listings from TripAdvisor,[16] mapping this information to ZIP-5 areas to create a metric for the number of vacation rental listings in a given market. Of course TripAdvisor's listings only reflect a fraction of the online vacation rental industry's total penetration; the underlying assumption here is that TripAdvisor's penetration and growth are reasonably proportional to the vacation rental industry's as a whole both across markets and over time.

I also utilize TripAdvisor to collect information on the type of travelers who visit a given market. Specifically, I attempt to match each hotel from the Hotels.com data with its corresponding TripAdvisor record based on name and address.[17] I then collect summary statistics for reviews at each hotel by traveler type (most importantly, the number/percent of reviewers who are business travelers) and by language in which the review was written (specifically, I utilize non-English-language reviews as a proxy for international travelers at a property).[18] These statistics are then aggregated by ZIP-5 area to create a metrics for the

[13] http://www.str.com/Media/Default/Research/STR_AirbnbHotelPerformance.pdf

[14] See Section 2.3 for more information on TripAdvisor.

[15] TripAdvisor 10-K filings

[16] I use TripAdvisor as a data source rather than Airbnb for logistical reasons – it is extremely difficult to collect comprehensive data from Airbnb's website.

[17] The ultimate match rate was quite good at just above 95%.

[18] Hotels.com provides some of the same aggregation metrics, but there are a number of reasons for using TripAdvisor's metrics here instead. For one, TripAdvisor has many more reviews than Hotels.com. For

type of travelers who visit particular markets.[19]

Table 1.1: Summary Statistics

	Firm-Level				
	Obs	**Mean**	**St. Dev.**	**Min**	**Max**
resort_fee	80,582	0.058	0.234	0.000	1.000
wifi_fee	80,582	0.050	0.217	0.000	1.000
stars	80,582	2.576	0.614	1.000	5.000
chain	80,582	0.636	0.481	0.000	1.000
rooms	80,582	106.3	145.5	1.000	5,000
roomshare	80,582	0.210	0.256	0.001	1.000
	Market-Level				
	Obs	**Mean**	**St. Dev.**	**Min**	**Max**
hotel_comps[a]	80,582	1.292	1.835	0.000	16.70
vrs[a]	80,582	1.420	4.125	0.000	49.31
pc_business	80,582	0.215	0.117	0.000	1.000
pc_english	80,582	0.959	0.060	0.165	1.000
log_pop	80,582	13.00	0.923	5.911	14.88
log_popdens	80,582	5.799	1.899	-2.086	11.52
nonhotel_estab	80,582	897.3	746.2	0.000	7,328
enplanements	80,582	7.224	9.346	0.203	44.39
seasonality	80,582	1.530	0.341	1.215	3.712

The unit of observation is the firm-period; unless otherwise noted, all summary statistics and regressions include data from two periods (April 2015 and April 2017) for 40,291 firms.

[a] *To improve readability of coefficients in regression analysis, the number of hotel competitors is measured in* ***units of ten****, and the number of vacation rentals is measured in* ***units of one hundred****.*

Finally, I draw additional market-level data from the U.S. Census Bureau (population, population density, and establishments by NAICS code at the ZIP-5 level for 2015) and the Bureau of Transportation Statistics (monthly enplanements for major hubs in 2015). This data is time invariant, thus the corresponding variables are absorbed in regressions

example, matched properties in my sample have on average 396 reviews on TripAdvisor but only 186 on Hotels.com. Similarly, there are 6,266 properties in my sample with fewer than 10 reviews on Hotels.com versus 877 with fewer than 10 reviews on TripAdvisor. Moreover, Hotels.com does not require reviewers to specify their trip type when writing a review, resulting in a large number of "unspecified" trip types.

[19] I do not utilize these metrics at the individual hotel level (e.g., the percent of reviewers at hotel i who identify as business travelers), as the type of travelers who stay at a particular hotel is potentially endogenous to the obfuscation decision (e.g., a hotel might opt not to charge a resort fee because it caters to business travelers, or, alternatively, business travelers might avoid certain hotels *because* they charge resort fees). At an aggregate market level, however, I argue that this type of endogeneity is very unlikely: travelers do not make choices about which *locations* to visit based on whether or not obfuscation is prevalent – rather, firms choose optimal levels of obfuscation based on the type of travelers who tend to visit their market.

Table 1.2: Correlation Matrix for Key Variables

	resort_fee	*wifi_fee*	*hotel_comps*	*vrs*	*stars*	*rooms*	*chain*	*seasonality*
resort_fee								
wifi_fee	-0.018*							
hotel_comps	0.231*	0.025*						
vrs	0.227*	0.050*	0.415*					
stars	0.225*	0.207*	0.147*	0.202*				
rooms	0.198*	0.254*	0.130*	0.180*	0.387*			
chain	-0.212*	0.070*	-0.165*	-0.143*	-0.072*	0.068*		
seasonality	0.101*	-0.028*	0.091*	0.120*	0.005	-0.028*	-0.082*	
pc_business	-0.191*	0.105*	-0.255*	-0.185*	0.044*	0.120*	0.331*	-0.183*

* $p < 0.001$

that utilize market-level fixed effects. Summary statistics and a correlation matrix for key variables of interest are presented in Tables 1.1 and 1.2; Table A1 in the appendix provides detailed variable descriptions.

1.3.3 Key Market-Level Trends

Figure 1.2 illustrates the distribution of hotels in the continental U.S., with those charging resort fees denoted in yellow. Upon first impression, two visible trends emerge. Perhaps most apparently, resort fees tend to be prevalent in "leisure" markets: along the coast, up and down the Appalachian mountains, and in western areas famous for skiing, national parks, and casinos. This pattern will also appear in regression analysis: resort fee utilization is persistently higher in areas with a disproportionately low share of business travelers. (Table A6 in the Appendix offers more detailed statistics for those markets where resort fees are most prevalent.) A rigorous empirical analysis of the relationship between shrouding and traveler type falls outside the scope of this paper, but the finding is worth discussing briefly.

Leisure travelers (in contrast to business travelers) are more likely to book online via an OTA such as Expedia or Priceline (where base price is a key determinant of visibility in search rankings). They are also generally more price sensitive than business travelers, who tend to exhibit some degree of brand loyalty. In other words: hotels in leisure markets likely compete on *price* more vigorously. Thus, that resort fees are more prevalent in these markets fits quite nicely with the intuition that competitive pressure heightens firms' incentives to

Figure 1.2: Resort Fees in the Continental U.S.

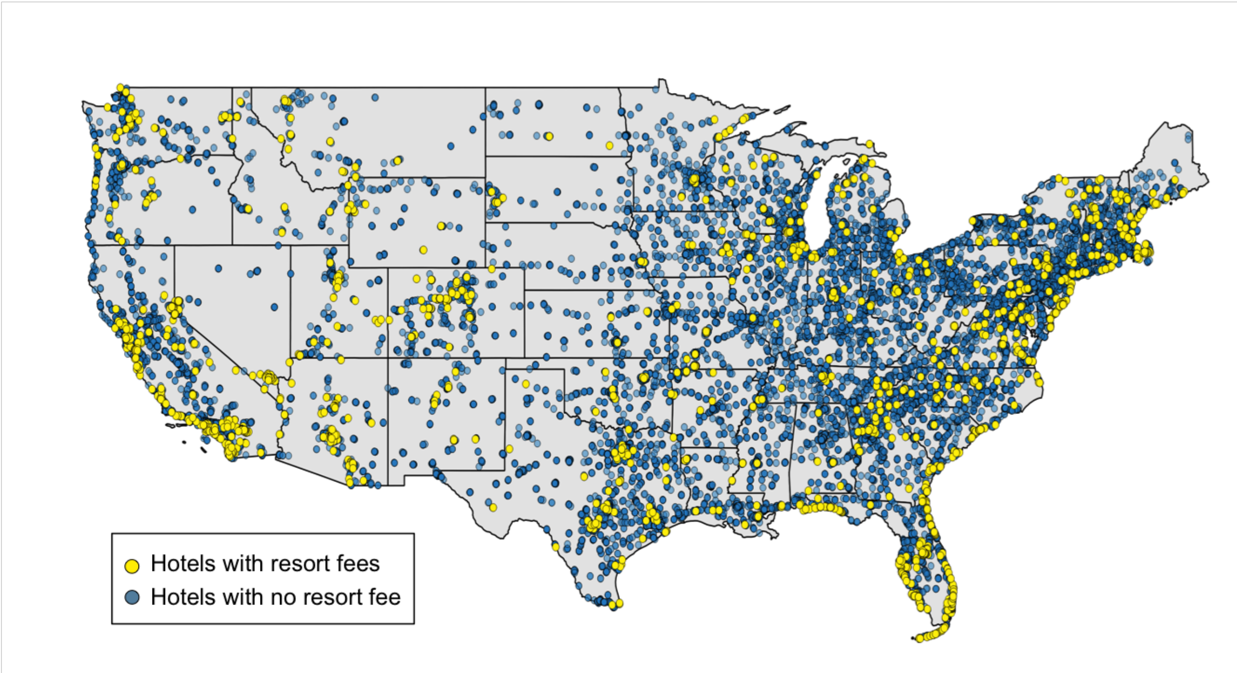


Table 1.3: Cross-Sectional Analysis of Variance (ANOVA)

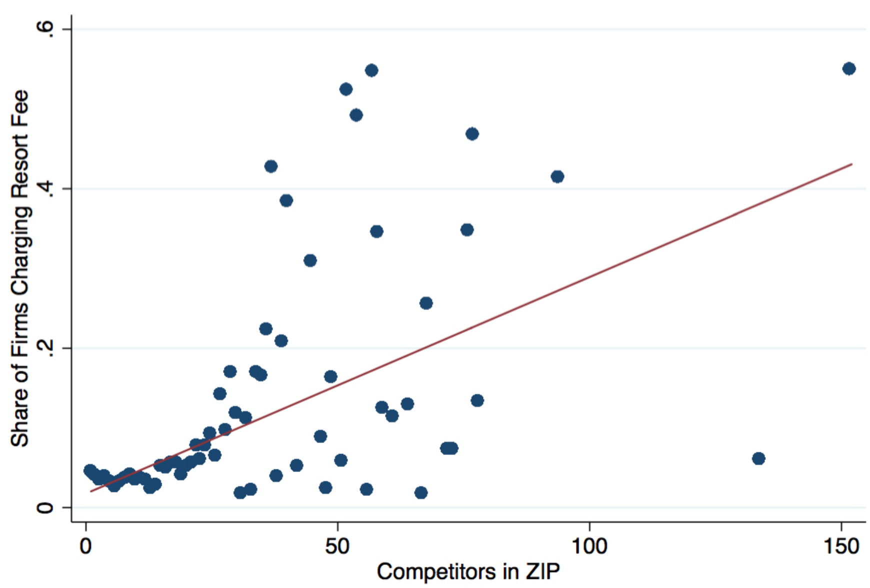
	Resort Fees		*WiFi Surcharges*	
	Partial SS	**Partial R-Squared**	**Partial SS**	**Partial R-Squared**
Model	382.6	0.192	884.4	0.434
metro	182.1	0.091	31.0	0.015
chain	68.2	0.034	717.7	0.352
stars	48.5	0.024	14.4	0.007
Residual	1612.4	0.808	1151.8	0.566
Total	1995.0	1.000	2036.2	1.000

Note: *metro* indicates fixed effects at the MSA-level, and *chain* indicates fixed effects at the chain level; *stars* is continuous. Sample includes first period observations only.

obfuscate. In addition, leisure travelers are arguably less likely to be repeat customers – so from a reputation / customer loyalty perspective, firms ostensibly care less about engaging in practices like price obfuscation that customers clearly despise. Finally, if we think of business and leisure travelers as, respectively, "sophisticates" and "myopes" in a world *a la* Gabaix and Laibson (2006), then it again makes sense that we observe obfuscation increasing in prevalence with the share of myopic buyers in the market.

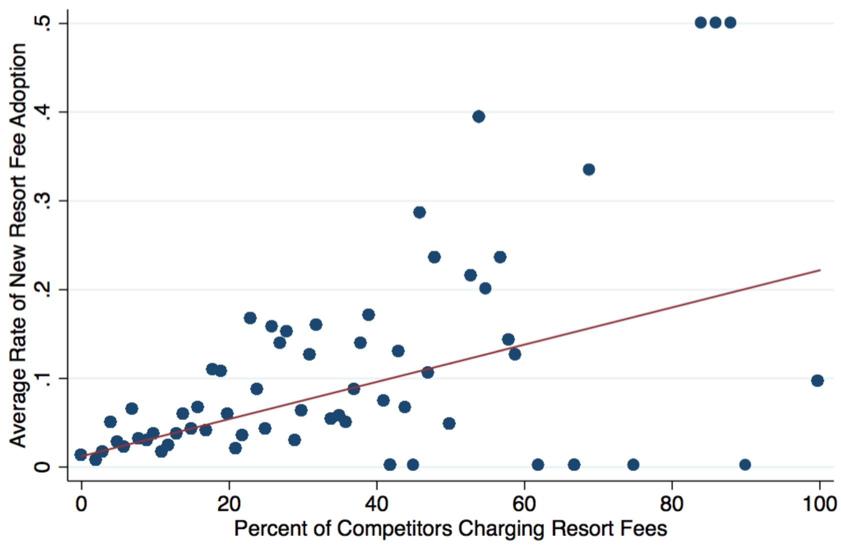
In any case, my primary focus here is not on the role of traveler type but rather on the role of market structure. The first indication that market-level forces may be an important determinant of shrouding is seen in Table 1.3: market-level fixed effects explain more of the variation in resort fee variation than chain-affiliation and star category combined. A closer look at Figure 1.2 suggests that competition, specifically, may play an important role in shaping the prevalence of shrouded pricing. Resort fees arise where competition is dense – even when the share of leisure travelers in the market is *not* disproportionately high (e.g., large cities like New York, Chicago, Boston, Atlanta, Indianapolis, San Antonio, etc.). Figure 1.3 hones in on this trend, plotting the average share of firms charging a resort fee against the number of hotel competitors in a ZIP-5 market. The positive correlation between competition and obfuscation is quite striking. A similar pattern appears in Figure 1.4, which plots the average resort fee adoption rate (i.e., the percent of hotels that adopted resort fees during my

Figure 1.3: Resort Fees and Competitive Density



two-year sample window) against the percent of firms initially charging resort fees in the corresponding market. In this case, the strong positive correlation suggests strategic interaction, i.e., that a firm's decision to shroud is influenced by it's competitors' shrouding choices. In the following sections, I explore these correlations further utilizing a range of empirical strategies.

Figure 1.4: Potential Strategic Interaction in Resort Fee Utilization



1.4 Empirical Specifications and Results

My analysis focuses on two primary empirical questions: first, how does competition affect firms' propensity to utilize shrouded pricing? Second, within a given market, does strategic interaction between firms influence shrouding decisions among competitors? Finally, I end this section with some broad descriptive evidence on trends in the adoption (and discontinuation) of shrouded pricing in the hotel industry and discuss additional factors other than competition that may be important to consider.

1.4.1 Competition and Shrouding

1.4.1.1 A Specification with Fixed Effects

To empirically investigate the relationship between competition and shrouding, I exploit both cross-sectional and time-series variation in competitive conditions (i.e., the number of hotels and vacation rental competitors that a firm faces). As a starting point, I estimate the following linear probability model for firm i in market j at time t:

$$shrouded\_charge_{it} = \beta_0 + \beta_1(hotel\_comps_{jt}) + \beta_2(vrs_{jt}) + x'_{it}\alpha + x'_{jt}\gamma + \delta_j + \nu_t + \varepsilon_{it} \qquad (1.1)$$

Here, x_{it} and x_{jt} are, respectively, vectors of observable firm and market characteristics, while δ_j and ν_t are fixed effects for market and period. Tables 1.4 and 1.5 present results for this specification for resort fees and WiFi fees, respectively.

In Tabel 1.4, we see that the utilization of resort fees is positively correlated with both measures of competition. An additional 10 hotels in the market are associated with a 1.4 percentage-point increase in the likelihood that firms charge resort fees[20] (a rather substantial difference – the average resort fee utilization rate across the two sample periods pooled is about 6%), and an additional 100 vacation rentals are associated with an increase of 0.5 percentage-points or so. The statistical significance of these correlations is quite robust. And while the magnitudes of the coefficient estimates fall slightly with the introduction of firm-level controls, they thereafter remain stable as market-level controls and fixed effects are introduced. (Indeed, the magnitude of the estimated coefficient actually increases when ZIP-5 fixed effects are added to the model.) The significance of the relationship is also robust to specifications of alternative functional form (e.g., a probit specification in Regression 6), although the estimated marginal effect in this case is lower than with OLS.

Other notable variables with strong correlations to resort fee utilization are chain affiliation and the percent of travelers in the market who are business travelers – both of which are

[20] In Table A8 in the appendix, results are substantively robust to alternative definitions of competition.

negatively associated with shrouding. The way in which traveler type might influence obfuscation is discussed in the preceding section, and the sign of the coefficient estimate here is as expected.[21] Similarly, the chain affiliation result is consistent with the perspective that reputation and customer loyalty concerns mitigate obfuscation as argued in Chiles (2017).

Regarding identification, it is important to clarify that these regressions treat competition as an exogenous variable. In practice, competitive conditions and the prevalence of obfuscation may both depend on omitted variables (particularly at the market level).[22] While results are robust to the incorporation of quite granular market-level fixed effects, this does not rule out the possibility that unobserved market-specific *changes* in demand or cost conditions over time may be correlated with both changing competitive conditions and changes in firms' propensity to obfuscate. In this sense, coefficients should not be interpreted as causal.

I argue, however, that unobserved factors that could influence both competitive conditions and obfuscation are more likely to bias the coefficient estimates here towards zero rather than away. For example, two leading candidates for why the number of competitors in a given market might increase are 1) demand growth and 2) an increase in the heterogeneity of buyer preferences. In the absence of entry, both of these scenarios should arguably *reduce* competitive pressure – not increase it. In other words, unobserved factors that are positively correlated with entry are likely negatively correlated with competitive intensity, all else equal. If this is the case, then coefficient estimates on the competition variables obtained in Table 1.4 will actually understate the effect of competition.

Moreover, it is useful that we have here two unique measures of competition. The

[21] While more leisure travelers in the market increases the prevalence of obfuscation, the share of international travelers (proxied by the share of non-English-language reviews) is not a significant predictor in most specifications. Leisure travelers and international travelers are similar in that they are both 1) less likely to be repeat customers and 2) arguably more likely to be "myopic" – i.e., to fail to notice hidden fees when booking. They are likely *different*, however, in their degree of price sensitivity (leisure travelers likely being more price sensitive than business travelers, but international travelers likely *less* price sensitive than domestic).

[22] Another potential concern is reverse causality, i.e., that obfuscation might actually induce entry. If obfuscation raises markups and thus industry profits, then this is a legitimate concern in theory. In this particular setting, however, the high proportion of fixed costs in the industry arguably lessens the likelihood that obfuscation is a meaningful driver of entry in practice. After controlling for other market characteristics, I find no evidence in my data that entry rates are higher in markets where obfuscation is more prevalent.

Table 1.4: Resort Fees and Competition

	Binary Dependent Variable: Resort Fees Charged?					
	OLS					*Probit*
	(1)	(2)	(3)	(4)	(5)	(6)
hotel_comps	0.021***	0.014**	0.014***	0.014***	0.026***	0.002**
	(0.005)	(0.004)	(0.003)	(0.03)	(0.008)	(0.01)
vrs	0.009***	0.004***	0.003***	0.003***	0.002***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
stars		−0.008**	−0.007**	−0.007**	−0.007*	−0.001
		(0.000)	(0.003)	(0.003)	(0.004)	(0.001)
rooms		0.000	0.000	0.000	0.000**	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
chain		−0.049***	−0.049***	−0.049***	−0.052***	−0.031***
		(0.003)	(0.003)	(0.003)	(0.005)	(0.002)
roomshare		0.020*	0.021*	0.021*	−0.008	−0.000
		(0.011)	(0.011)	(0.011)	(0.018)	(0.005)
any_comps			0.019**	0.019**	0.005	0.004
			(0.008)	(0.08)	(0.010)	(0.004)
pc_comps_chain			−0.009*	−0.009*	−0.013	−0.007***
			(0.005)	(0.005)	(0.009)	(0.003)
seasonality			0.029***	0.029***		0.009***
			(0.008)	(0.008)		(0.002)
pc_business			−0.088***	−0.087***		−0.085***
			(0.014)	(0.014)		(0.009)
pc_english			−0.032	−0.032		−0.047***
			(0.034)	(0.034)		(0.012)
Add'l Firm Controls	No	Yes	Yes	Yes	Yes	Yes
Add'l Market Controls	No	No	Yes	Yes	Absorbed	Yes
Market Fixed Effects	No	No	MSA	MSA	ZIP-5	No
Time Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	80,582	80,582	80,582	80,582	80,582	80,582
R-squared	0.07	0.25	0.29	0.29	0.40	NA

Standard errors in parentheses reflect clustering at the ZIP-5 level
(8,864 clusters)
*** p<0.01, ** p<0.05, * p<0.1

Note that the number of hotel competitors (hotel_comps) is measured here in units of ten; the number of vacation rentals (vrs) is measured in hundreds. Regression (6) presents marginal probit effects, evaluated at explanatory variable mean values.

unobserved factors that drive growth in the number of hotel competitors are often different from the factors that drive growth in the online vacation rental sector. And even when the same factors affect both competitive metrics, the *direction* of the effect may be different. For example, unemployment should depress the hotel sector, slowing entry, but may actually increase the entry rate for vacation rentals, as more individuals look to rent out their homes as a source of income. That coefficient estimates on both of the competition variables are robustly positive then, is quite compelling, as the potential that an omitted variable is driving *both* sets of results seems unlikely.

The results for WiFi fees in Table 1.5 stand in stark contrast to those for resort fees. Here, there seems to be no correlation with competition – if anything, coefficient estimates are slightly negative for both $hotel\_comps$ and vrs. Indeed, subsequent empirical sections do not include separate analyses for WiFi fees as this story remains consistent in other specifications as well: there is no persistent empirical relationship between competition and the utilization of WiFi fees, nor is there any evidence that strategic interaction between firms shapes their propensity to adopt these fees.

It is worth briefly discussing the factors that *are* correlated with the adoption of WiFi surcharges – particularly those that differ from the resort fee results. First, unlike resort fees, WiFi fees *increase* in prevalence with the share of business travelers in the market. This makes very little sense in the context of the discussion in Section 1.3.3. Business travelers are less price-sensitive and less likely to book on OTA websites, so firms should feel less pressure to mislead these customers with a deceptively low up-front price. Moreover, business travelers are more likely to be repeat customers, so deceiving them is more costly if it results in a loss of business in future periods. Finally, business travelers are likely to be more savvy (i.e., the "sophisticates," as opposed to the "myopes"). They travel more often and are thus more experienced in knowing where to look for hidden fees and how to avoid them. Firms have less of an incentive to attempt to deceive these travelers, as fewer of them will fall for the deception. Similarly, the positive coefficient on chain affiliation does not seem consistent with the view that WiFi charges are a form of shrouded pricing. If we believe that reputational concerns decrease chain-affiliated firms' incentives to obfuscate (as they seem to do with resort fees), then this result is rather puzzling.

Taken together, these results cast doubt on the characterization of optional add-ons as "shrouded pricing." What they *do* bring to mind, however, is the scenario of add-on

Table 1.5: WiFi Fees and Competition

	Binary Dependent Variable: WiFi Fees Charged?					
	OLS					*Probit*
	(1)	(2)	(3)	(4)	(5)	(6)
hotel_comps	0.001 (0.001)	−0.005∗∗∗ (0.001)	−0.002∗ (0.001)	−0.002∗ (0.001)	−0.001 (0.004)	−0.001 (0.001)
vrs	0.003∗∗∗ (0.001)	−0.001∗∗ (0.000)	−0.001∗∗ (0.000)	−0.001∗ (0.000)	−0.001∗ (0.000)	−0.000 (0.000)
stars		0.045∗∗∗ (0.003)	0.044∗∗∗ (0.003)	0.045∗∗∗ (0.003)	0.047∗∗∗ (0.004)	0.021∗∗∗ (0.001)
rooms		0.000∗∗∗ (0.000)	0.000∗∗∗ (0.000)	0.000∗∗∗ (0.000)	0.000∗∗∗ (0.000)	0.000∗∗∗ (0.000)
chain		0.072∗∗∗ (0.003)	0.071∗∗∗ (0.003)	0.071∗∗∗ (0.003)	0.078∗∗∗ (0.004)	0.026∗∗∗ (0.001)
roomshare		0.008∗ (0.004)	0.041∗∗∗ (0.011)	0.040∗∗∗ (0.011)	0.172∗∗∗ (0.031)	0.018∗∗∗ (0.004)
any_comps			0.012 (0.009)	0.012 (0.009)	0.061∗∗∗ (0.012)	0.005 (0.004)
pc_comps_chain			0.017∗∗∗ (0.004)	0.016∗∗∗ (0.004)	0.042∗∗∗ (0.008)	0.007∗∗∗ (0.002)
seasonality			−0.001 (0.006)	−0.001 (0.006)		−0.001 (0.002)
pc_business			0.129∗∗∗ (0.017)	0.130∗∗∗ (0.017)		0.045∗∗∗ (0.006)
pc_english			−0.019 (0.028)	−0.019 (0.028)		−0.033∗∗∗ (0.010)
Add'l Firm Controls	No	Yes	Yes	Yes	Yes	Yes
Add'l Market Controls	No	No	Yes	Yes	Absorbed	Yes
Market Fixed Effects	No	No	MSA	MSA	ZIP-5	No
Time Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	80,582	80,582	80,582	80,582	80,582	80,582
R-squared	0.00	0.19	0.21	0.21	0.33	NA

Standard errors in parentheses reflect clustering at the ZIP-5 level
(8,864 clusters)
*** p<0.01, ** p<0.05, * p<0.1

Note that the number of hotel competitors (hotel_comps) is measured here in units of ten; the number of vacation rentals (vrs) is measured in hundreds. Regression (6) presents marginal probit effects, evaluated at explanatory variable mean values.

price discrimination described by Ellison (2005). Here, there are two types of consumers in the market – "high types" and "low types," and the high types have both stronger brand preferences in the market for the base good and a higher level of demand for add-ons. When these conditions hold, partitioning charges for the add-on good is jointly rational and raises equilibrium profits. But add-on pricing here is *not* obfuscation in the sense that consumers are not deceived (nor is the firms' intent to make information more difficult to discern). Rather, this strategy is about customer segmentation and the creation of an adverse selection problem that softens price competition in the market for the base good.

In the data here, we see avoidable add-on fees for WiFi increase in prevalence as the share of business travelers in the market grows. And, indeed, business travelers in the hotel setting are the quintessential embodiment of "high types." As previously discussed, these travelers tend to exhibit stronger brand preferences and are less likely to be sensitive to small differences in prices across firms. Moreover, they almost certainly have higher demand for the relevant add-on good (WiFi) than do leisure travelers, as many will simply expense this sort of charge to their employer's account. While I cannot offer definitive conclusions with regard to whether WiFi fees are truly price obfuscation or not, at the very least, I can conclude that shrouded pricing in the form of mandatory surcharges and shrouded pricing in the form of avoidable add-ons arise under very different sets of circumstances. More generally, it seems fair to question whether or not we should be thinking of WiFi fees and other avoidable add-on surcharges as price obfuscation at all, when in reality they seem to fit with price discrimination frameworks more closely.

1.4.1.2 A Difference-in-Differences-Style Specification

For the remainder of this paper, I focus solely on price obfuscation in the form of resort fees. In an effort to more accurately identify the effect of competition on shrouding, this section offers a comparison of outcomes at independent versus chain-affiliated hotels in a difference-in-differences-style framework. Specifically, I utilize chain-affiliated hotels as a pseudo "control group," under the assumption that chain hotels are *less* likely to respond to changes in competitive conditions but equally likely to react to unobserved demand and cost stimuli.[23] The former half of this assumption in particular seems quite robust. Chain-affiliated hotels benefit (to varying degrees) from customer loyalty, so all else equal, an additional entrant will steal *less* market share from a chain-affiliated firm than from an independent firm if some portion of the chain's customers are sticky. And in the case of vacation rentals, the argument is even stronger, as chains cater disproportionately to business travelers,[24] a subset of customers that is intuitively quite unlikely to substitute a hotel room for a vacation rental. Zervas and Proserpio (2014) confirm this intuition: Airbnb's financial impact on hotels that cater to business travelers is smaller in magnitude. The latter half of my identifying assumption – that chain hotels respond in the same way as non-chain hotels to other (unobserved) market factors – is less certain; a potential threat to identification is that the same factors which cause chains to respond differently to competition might also cause them to respond differently to other changes at the market-level.

Formally, I estimate a specification similar to the one detailed in Section 1.4.1.1, with the key addition of interaction terms to capture differences in outcomes for "treated" firms (independent hotels) versus "control group" firms (chain-affiliated hotels):

$$\begin{aligned} shrouded\_charge_{it} = \beta_0 + \beta_1(chain_{it}) + \beta_2(hotel\_comps_{jt}) + \beta_3(chain_{it} * hotel\_comps_{jt}) \\ + \beta_4(vrs_{jt}) + \beta_5(chain_{it} * vrs_{jt}) + x'_{it}\alpha + x'_{jt}\gamma + \delta_j + \nu_t + \varepsilon_{it} \quad (1.2) \end{aligned}$$

Table 1.6 presents estimation results for this specification. (When interpreting coefficients, note that the indicator for whether or not a firm is in the "treatment group" is coded in reverse of the typical way – chains are the control group in this particular specification, but they are coded in the data as *chain=1*.) Competition from other hotels remains positively

[23]My approach here is similar in spirit to Seamans and Zhu (2014), who study the impact of Craigslist on local newspapers. Here, the authors identify a subset of newspapers who should be *less* responsive to the entry of Craigslist and utilize this set as a control group in a difference-in-differences framework.

[24]In my data, business travelers account for 14% of reviews at independent properties versus 25% at chain-affiliated hotels.

associated with resort fee utilization for both chains and non-chains, but the effect is markedly stronger for non-chains. An additional 10 hotel competitors results in an increase in resort fee utilization of 2.9 percentage points for non-chains and 2.0 percentage points for chains (i.e., a "treatment effect" of 0.9 percentage points). Similarly, an additional 100 vacation rentals is associated with a 0.3 percentage point increase in resort fees for non-chains but a slight decrease for non-chains (netting out to a "treatment effect" of 0.4 percentage points). Results here suggest that intra-industry competition's true effect on shrouding is a bit smaller than the fixed effects specification indicates (0.9 percentage points vs. 2.6). In the case of vacation rental competition, however, results here are slightly larger than in the fixed effects model (0.4 percentage points vs. 0.2).

This model is not a "true" difference-in-differences specification for two important reasons. For one, the "control group" likely absorbs some of the treatment. By this I mean that in reality, chain-affiliated hotels likely feel *some* increase in competitive pressure as more firms enter the market (indeed, this seems to be borne out empirically in the case of intra-industry competition). The assumption that chains do not receive any competitive "treatment" at all has the effect of biasing the estimated treatment effect here towards zero – so as with the fixed effects model, these estimates might arguably be thought of as lower bounds on the true magnitude of the effect of competition. On the other hand, a second potential issue is that chain hotels might be a poor proxy for a true control group if they react differently from independent hotels to market-level changes *other* than competition. This could potentially bias the coefficient estimate in either direction, depending on the nature of potential omitted variables. On net, however, the evidence from this and the preceding section seems compelling: in a wide range of specifications, competition is robustly associated with increased prevalence in shrouded mandatory surcharges.

Table 1.6: Differential Effect of Competition by Chain Affiliation

	Binary Dependent Variable: Resort Fees Charged?		
	(1)	(2)	(3)
chain	$-0.062***$	$-0.029***$	$-0.027***$
	(0.005)	(0.004)	(0.006)
hotel_comps	$0.021***$	$0.017***$	$0.029***$
	(0.006)	(0.002)	(0.009)
chain * hotel_comps	$-0.010***$	$-0.011***$	$-0.009**$
	(0.004)	(0.003)	(0.004)
vrs	$0.010***$	$0.005***$	$0.003***$
	(0.001)	(0.001)	(0.001)
chain * vrs	$-0.004***$	$-0.004**$	$-0.004**$
	(0.002)	(0.002)	(0.002)
stars		$-0.007**$	$-0.008*$
		(0.003)	(0.004)
rooms		0.000	$0.000***$
		(0.000)	(0.000)
roomshare		0.011	-0.014
		(0.011)	(0.017)
anycomps		0.012	-0.003
		(0.008)	(0.010)
pc_comps_chain		$-0.010**$	0.014
		(0.005)	(0.009)
seasonality		$0.027***$	
		(0.008)	
pc_business		$-0.097***$	
		(0.014)	
pc_english		-0.042	
		(0.033)	
Add'l Firm Controls	No	Yes	Yes
Add'l Market Controls	No	Yes	Absorbed
Market Fixed Effects	No	MSA	ZIP-5
Time Fixed Effects	No	Yes	Yes
Observations	80,582	80,582	80,582
R-squared	0.11	0.29	0.40

Standard errors in parentheses reflect clustering at the ZIP-5 level
(8,864 clusters)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note that the number of hotel competitors (hotel_comps) is measured here in units of ten; the number of vacation rentals (vrs) is measured in hundreds.

1.4.2 Strategic Interactions in Shrouding

In this section, I focus on the question of whether or not a firm's decision to adopt a resort fee in period $t+1$ depends on competitors' shrouding choices in period t.[25] In other words, I am interested in determining to what extent shrouding proliferates sequentially based on strategic interactions between firms. I wish to estimate the following model for firm i in market j:

$$shrouded\_charge_{i,t+1} = \beta_0 + \beta_1(pc\_comps\_shrouding_{jt}) + x_{it}'\alpha + x_{jt}'\gamma + \delta_j + \varepsilon_{it} \tag{1.3}$$

Here again, x_{it} and x_{jt} are, respectively, vectors of observable firm and market characteristics (x_{jt} will include the variables measuring competition discussed in detail in the preceding sections – *hotel_comps* and *vrs*). The central problem with this model is that firm i's shrouding decision is inherently endogenous to its competitors' decisions in the sense that omitted demand and/or cost factors likely influence both. Estimating this model as-is, a statistically signifiant estimate for β_1 might be indicative of strategic interaction. It could also simply reflect the relevance of unobserved factors that affect the propensity of *all* firms in market j to obfuscate.

To empirically separate the effect of strategic interactions from unobserved market-level factors, I instrument chain-affiliated competitors' propensity to obfuscate in market j with corresponding chain-level rates of obfuscation in other markets $(-j)$. The critical identifying assumption here is that there is within-chain correlation in shrouding, but that the choices chains make in other markets $(-j)$ have no direct effect on firm i's propensity to shroud in market j. This assumption seems robust. Consider two hotels in market j – a generic Hotel A, and a Hilton. The rate at which Hiltons in other markets adopt resort fees should have no effect on Hotel A, except to the extent that chain-level norms shape Hilton's obfuscation choices in market j.

[25] Note that in all regression specifications here, I restrict my sample to the set of firms that did not charge resort fees in the first period of the sample (38,186 firms).

Table 1.7: Out-of-Market Obfuscation Predicts In-Market Obfuscation *(First Stage)*

	Dependent Variable: Percent of Competitors Charging Resort Fee		
	(1)	(2)	(3)
chaincomps_othermkt_rfee	0.721∗∗∗	0.609∗∗∗	0.459∗∗∗
	(0.126)	(0.083)	(0.070)
anycomps_chain	0.031∗∗∗	−0.005	−0.001
	(0.009)	(0.008)	(0.007)
anycomps	0.031∗∗∗	0.047∗∗∗	0.050∗∗∗
	(0.009)	(0.009)	(0.007)
pc_comps_chain	−0.111∗∗∗	−0.061∗∗∗	−0.065∗∗∗
	(0.009)	(0.007)	(0.006)
hotel_comps		0.006	0.011∗∗∗
		(0.005)	(0.003)
vrs		0.010∗∗∗	0.007∗∗∗
		(0.001)	(0.001)
stars		0.004∗∗	0.003∗∗
		(0.002)	(0.001)
rooms		0.000	−0.000
		(0.000)	(0.000)
chain		0.003∗∗	−0.001
		(0.001)	(0.001)
roomshare		−0.021	−0.019∗∗
		(0.015)	(0.009)
seasonality		0.022∗∗∗	0.033∗∗∗
		(0.007)	(0.008)
pc_business		−0.074∗∗∗	−0.067∗∗∗
		(0.013)	(0.012)
pc_english		−0.167∗∗∗	−0.031
		(0.044)	(0.035)
Add'l Firm Controls	Yes	Yes	Yes
Add'l Market Controls	No	Yes	Yes
Market Fixed Effects	No	No	MSA
Observations	38,186	38,186	38,186
R-squared	0.22	0.30	0.44

Standard errors in parentheses reflect clustering at the ZIP-5 level *(8,720 clusters)*

*** p<0.01, ** p<0.05, * p<0.1

Note that the number of hotel competitors (hotel_comps) is measured in units of ten; the number of vacation rentals (vrs) is measured in hundreds.

To achieve this empirically, I construct a metric that aggregates all relevant chain-affiliated competitors' propensities to obfuscate in *other* markets.[26] Table 1.7 presents first-stage results. The relationship between the instrument (the rate at which chain-affiliated competitors utilize resort fees in other markets in period t) and our endogenous variable of interest (the percent of competitors in market j that utilize resort fees in period t) is positive and significant. T-statistics for the instrument in the second two specifications are 7.4 and 6.6, respectively.

Second-stage results are found in Table 1.8. Columns (1) through (3) present the reduced-form relationship between firm i's resort fee utilization in period $t+1$ and competitors' resort fee utilization in period t. Columns (4) and (5) present two-stage-least-squares instrumental variable estimation results. The main finding here is that strategic interactions between firms seem to be quite important – the coefficient on *pc_comps_rfee* is positive, highly significant, and *more* significant after instrumentation, even with the introduction of MSA-level fixed effects.[27] If competitors' propensity to charge resort fees increases by ten percentage points, firm i's propensity to shroud increases by 3.6 percentage points. The coefficient estimate on *hotel_comps* also remains marginally significant in these specifications (i.e., competition today is correlated with obfuscation tomorrow), although the coefficient on *vrs* does not.[28]

[26] I follow Jin (2005) in my approach here. For each chain-affiliated competitor, I compute the average resort fee utilization rate for the corresponding chain in all markets ($-j$); I then average this statistic over all chain-affiliated competitors in market j. In practice, this metric needs to be accompanied by several others to make sense. In all specifications, I continue to include the indicator variable *anycomps*, which resolves the problem of missing values in cases where hotels have no competitors. I also continue to include *pc_comps_chain*, which accounts for the share of competitors whose obfuscation behavior can be instrumented with out-of-market comparables. Finally, I include an indicator variable, *anycomps_chain* to deal with missing values for the instrument in cases where a hotel has competitors but no chain-affiliated competitors. All of these additional variables, however, are not utilized as instruments – they are also included on the right-hand side of the main specification.

[27] Note that I cannot include ZIP-5 fixed effects here, since measures of competition and strategic interaction are defined at the ZIP-5 level, and results are based on only one period (rather than a panel).

[28] Again, note that this specification is different from prior specifications in that it is structured to predict shrouding in period $t+1$ (conditional on firms *not* shrouding in period t). Alternatively, prior specifications were structured to test the relationship between competition in period t and obfuscation in period t.

Table 1.8: Strategic Interaction in Resort Fee Decisions

	Binary Dependent Variable: Resort Fee in Final Period				
	Probit	*OLS*		*IV-2SLS*	
	(1)	(2)	(3)	(4)	(5)
pc_comps_rfee	0.021***	0.102***	0.069***	0.365***	0.355**
	(0.004)	(0.018)	(0.015)	(0.134)	(0.152)
hotel_comps	0.001	0.006*	0.008***	0.004*	0.005*
	(0.000)	(0.003)	(0.003)	(0.002)	(0.003)
vrs	0.000	0.001	−0.001	−0.002	−0.003
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
stars	0.002**	0.004*	0.004*	0.003	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
rooms	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
chain	−0.008***	−0.012***	−0.013***	−0.013***	−0.013***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
roomshare	−0.002	0.014	0.013	0.019**	0.018**
	(0.004)	(0.011)	(0.009)	(0.010)	(0.009)
anycomps	−0.004	−0.001	0.002	−0.013	−0.012
	(0.003)	(0.007)	(0.006)	(0.009)	(0.010)
pc_comps_chain	−0.007***	−0.003	−0.008*	0.016	0.013
	(0.002)	(0.005)	(0.005)	(0.010)	(0.012)
seasonality	0.001	0.002	0.007	−0.003	−0.003
	(0.001)	(0.004)	(0.006)	(0.005)	(0.008)
pc_business	−0.033***	−0.023***	−0.031***	−0.005	−0.015
	(0.006)	(0.009)	(0.011)	(0.013)	(0.014)
pc_english	−0.023***	−0.082***	−0.012	−0.035	−0.004
	(0.007)	(0.028)	(0.027)	(0.034)	(0.028)
Add'l Firm Controls	Yes	Yes	Yes	Yes	Yes
Add'l Market Controls	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	No	No	MSA	No	MSA
Observations	38,186	38,186	38,186	38,186	38,186
R-squared	NA	0.07	0.10	NA	NA

Standard errors in parentheses reflect clustering at the ZIP-5 level
(8,720 clusters)
*** p<0.01, ** p<0.05, * p<0.1

*Note that the number of hotel competitors (hotel_comps) is measured here in units of ten; the number of vacation rentals (vrs) is measured in hundreds. Regression (1) presents marginal probit effects, evaluated at explanatory variable mean values. In regressions (4) and (5), the rate at which competitors charge resort fees in market **j** (pc_comps_fee) is instrumented with chain competitors' propensity to charge resort fees in other markets (**-j**).*

1.4.3 What Other Factors Might Drive Shrouding?

Before concluding, it is worth briefly exploring the hotels that adopt or discontinue resort fees (and their corresponding markets) in a bit more depth. I begin with discontinuations. While substantially fewer hotels discontinued resort fees than adopted them, the discontinuation *rate* is actually rather substantial: of the 2,105 hotels that charged a resort fee as of April 2015, 297 dropped the fee by April 2017. Upon further inspection, 9 of these firms correspondingly adopted other mandatory fees (cleaning fees, most commonly) – in other words, they simply renamed their shrouded surcharges. Of the remaining firms, 11.5% changed their listed name and/or chain affiliation during the sample window versus 5.9% of the firms that did *not* drop, suggesting that changes in management play an important role.

Turning to adoptions, the preceding section establishes that shrouding behavior should proliferate sequentially, and it is, indeed, the case that most firms who adopt resort fees are located in markets where other firms are already engaging in this practice. Specifically, of the 786 firms that adopted a resort fee between April 2015 and April 2017, 56% (90%) are located in ZIP-5 markets (MSA markets) where at least one competitor was already charging a fee. The 10% of adopters located in MSA markets where resort fees previously did not exist are a particularly interesting case. Compared with resort fee "followers," adopters in these "virgin" markets tend to be smaller, niche properties (e.g., B&B's) in rural areas. Adopters in virgin markets also tend to face *less* competitive environments: only 80.5% of these firms compete with at least one other firm in their ZIP-5 area, versus 94.9% for follow-on adopters. This last finding suggests that while competitive conditions may be an important driver of shrouded pricing, there are critical firm-specific factors at work as well. This is an area that warrants further research.

1.5 Conclusions

This paper presents novel empirical evidence on the relationship between competitive conditions and price obfuscation. Using data from the U.S. hotel industry, I show that firms' propensity to charge resort fees (a mandatory shrouded surcharge) increases 1) as the number of competitors in the market grows, and 2) as a larger share of competitors obfuscate. These findings are in line with Shleifer's (2004) argument regarding the relationship between market conditions and ethically questionable behavior: firms in markets where profits are lower (in this case, ostensibly due to more intense competition) will be more likely to engage in obfuscation, and, moreover, once one firm begins to obfuscate others are more likely to follow suit. Importantly, empirical results on the relationship between price obfuscation and the number of competitors in a market should be interpreted as correlational rather than causal. Though findings are robust to a wide range of empirical specifications, I can not definitively rule out the possibility that some omitted variable may be driving the observed relationship between competition and obfuscation. Identification is more sound, however, in the specifications testing the relevance of strategic interaction among firms, as this approach relies on an instrumental variables strategy.

The results obtained for resort fees stand in notable contrast to the corresponding results for WiFi fees (an avoidable shrouded charge), where there appears to be no empirical relationship whatsoever between competition and obfuscation. Indeed, the difference is so striking that it seems fair to call into question whether or not WiFi fees in this context ought to be thought of as price obfuscation at all. If we define obfuscation as involving an *intent* to mislead, it's nearly impossible to say one way or the other, but certainly the empirical circumstances under which mandatory and avoidable surcharges arise seem to be quite different. My motivation in drawing this distinction is not to argue that avoidable surcharges should *never* be labeled as price obfuscation. Rather, my hope is to underscore the importance of thinking carefully about what practices we as researchers categorize as obfuscation in the first place. For both academics and policy-makers, this distinction may matter a great deal, and future research should work to develop more structured theoretical and empirical criteria for determining what constitutes price obfuscation in practice.

CHAPTER 2

Shrouded Prices and Firm Reputation

2.1 Introduction

Recent theoretical contributions in both economics and strategic management make the case that price obfuscation is optimal in many settings (e.g., Ellison, 2005; Gabaix and Laibson, 2006; Spiegler, 2006; Carlin, 2009; Ellison and Wolitzky, 2012; Chioveanu and Zhou, 2014), and empirical evidence seems to confirm that price obfuscation strategies are highly effective at boosting demand and markups (e.g., Morwitz, Greenleaf, and Johnson, 1998; Hossain and Morgan, 2006; Ellison and Ellison, 2009; Brown, Hossain, and Morgan, 2010; Kalayci and Potters, 2011). That obfuscation tactics have become commonplace in many industries is, perhaps, a testament to the cogency of these authors' findings. More broadly, however, there is a clear disconnect between existing research and empirical reality: a mounting body of evidence confirms its advantages, yet price obfuscation is far from universal in practice. Instead, its prevalence varies widely both within and across industries. Plainly put, some firms obfuscate, and some do not. How might this be explained? Under what conditions and to what extent might market forces fully or partially counteract the incentives that motivate firms to obfuscate?

The literature on reputation and relational contracting has emphasized the way in which potential loss of future business can incentivize honesty in transactions (e.g., Tesler, 1980; Klein and Leffler, 1981; MacLeod, 2007). Perhaps, then, reputational concerns may mitigate the motivation to obfuscate if consumers perceive these tactics as deceptive and subsequently punish the offending firms. In repeated transaction settings, embittered consumers might simply take their business elsewhere. Alternatively, some markets provide consumers with the ability to punish via publicly observable negative feedback (e.g., via rating mechanisms such as Yelp or TripAdvisor). Here, firms may have an incentive to avoid obfuscation even if interactions are not repeated and the set of buyers in the market is different each period.

This chapter focuses on the latter set of circumstances and attempts to shed light on the potential reputational consequences of one specific type of price obfuscation – shrouded surcharges.[1] My empirical setting is the U.S. hotel industry, where the increasing prevalence of hidden fees has provoked substantial negative media attention and regulatory scrutiny in recent years. Of particular interest are "resort fees," which are mandatory surcharges imposed by roughly 7% of hotels. These fees are typically shrouded in fine print, and both news coverage and actual traveler review content indicates that many consumers are unaware of them at the time of booking. Instead, uninformed consumers find out about resort fees upon arrival at the hotel, or even, in some cases, upon check-out when receiving their final bill – anecdotally, at least, resulting in substantial indignation. To empirically quantify this "hidden fee effect" on firm reputation, I utilize online ratings (i.e., publicly observable scores that hotel travelers submit about their experience *ex post*) from two sources: Expedia and TripAdvisor.

I first document a robust negative relationship between resort fees and average traveler ratings in cross-sectional data. While this negative association persists even after controlling for observable firm and market characteristics, there is ample reason to be concerned that a firm's decision to charge resort fees may be correlated with unobserved factors that affect ratings (e.g., quality of facilities, management, etc.) or that having a lower reputation is actually what causes these firms to adopt resort fees in the first place. To address these issues, I exploit differences in surcharge disclosure across booking channels. For a subset of hotels, Expedia's booking platform actually includes resort fees in the price that travelers must pay up front – in other words, resort fees are unshrouded for customers booking these

[1] The practice of obfuscating the total price of a good by breaking it into multiple (partially shrouded) components has been referred to in various literatures by a number of terms: drip pricing, partitioned pricing, add-on pricing, etc. In this paper, I most often refer simply to "hidden fees."

hotels through Expedia. And since travelers must have verifiably booked through an Expedia interface to submit an Expedia review, ratings on Expedia effectively serve as a control group for this hotel subset. In contrast, resort fees *are* hidden from consumers booking these same hotels via almost all other channels. Any associated "hidden fee effect" will accordingly be reflected in more negative reviews on sites such as TripAdvisor, where travelers from many different booking channels submit ratings.

This unique feature of the online hotel booking market allows me to estimate the causal effect of hidden fees in a difference-in-differences framework. By collecting repeated monthly cross-sections of hotel characteristics, I observe when a hotel adopts (or drops) a resort fee that is *not* hidden on Expedia but *is* hidden in other settings. Focusing on this key subset of hotels, I then compare time-stamped individual traveler reviews from Expedia (the control group) to those from TripAdvisor (the treatment group) pre- and post-policy change. Both groups of reviews absorb any potential unobserved shocks in quality correlated with changes in resort fee policy, but only TripAdvisor reviews reflect the actual effect of hidden fees on ratings.

Results from this analysis indicate that hidden fees reduce traveler ratings by roughly 0.15 points (on a rating scale that ranges from 1 to 5). Applying benchmarks from existing literature (e.g., Luca, 2011; Anderson, 2012; Expedia, 2012), the revenue loss associated with this baseline decline in ratings is in the ballpark of 1-2% – a non-trivial amount, but still likely not enough in many cases to outweigh the revenue *gains* associated with the adoption of a hidden fee. The magnitude of the estimated effect on ratings varies substantially, however, depending on firm characteristics. In particular, lower-end hotels that adopt resort fees are punished much more severely than their higher-end counterparts. This finding helps to explain observed variation in resort fee adoption patterns within the broader market, where lower-end hotels rarely adopt these surcharges.

That hidden fees are roundly detested by consumers is both intuitive and well documented in popular press. Yet there is surprisingly little empirical evidence that this animosity results in any tangible negative consequences for firms. This paper, then, makes several key contributions. Firstly, I provide causal evidence in support of the notion that shrouded surcharges can result in reputational damage. This finding is especially important given the existing literature's overwhelming focus on the financial benefits of obfuscation. Results here underscore the fact that there are trade-offs: shrouded surcharges are not all upside and should be implemented with care. Secondly, the treatment effect that I estimate varies substantially depending on firm characteristics. This helps to explain observed heterogeneity (when expected punishment is large, firms are less likely to adopt hidden fees) and, more generally, begins to build toward a broader conceptual framework for thinking about why some firms adopt price obfuscation and some do not. Finally, it is critical for managers to understand the potential relevance of reputational cost when considering the implementation of deceptive tactics (both in pricing and more generally). Reputation is often an important strategic asset, and online ratings, in particular, have been shown to be highly effective drivers of revenue and markups (e.g., Resnick et al., 2006; Cabral and Hortacsu, 2010; Luca, 2011). Indeed, online ratings are likely to be more influential than ever going forward, as consumers increasingly rely on them when making purchase decisions.

The remainder of this chapter is structured as follows: In Section 2.2, I highlight findings from several related bodies of literature that, together, provide the motivation for this paper. Section 2.3 offers a brief overview of the workings of the U.S. hotel industry relevant to the present empirical analysis (including some background on Expedia and TripAdvisor – the two sources of data utilized here). Section 2.4 underscores broad cross-sectional evidence in support of the hypothesis that hidden fees result in lower ratings. The core empirical analysis is contained in Section 2.5; here, I introduce the difference-in-differences (D-in-D) model, present estimates for the causal effect of hidden fees on ratings, and discuss key empirical findings. Section 2.6 concludes by summarizing the contributions of this paper to both theory and practice.

2.2 Motivation and Prior Literature

2.2.1 The Case For Obfuscation: Theory and Empirical Evidence

> *"Competitive markets by their very nature spawn deception and trickery, as a result of the same profit motives that give us our prosperity."*
>
> \- George Akerlof and Robert Shiller (2015)[2]

Both the theoretical and empirical literature on price obfuscation have, to date, been heavily focused on understanding the financial gains that motivate firms to obfuscate.[3] Theoretical work can largely be unified under a single common theme: obfuscation exists in equilibrium because at least some consumers fail to accurately assess prices when faced with these tactics. In some cases, this is because consumers are boundedly rational – they are myopic (e.g., Gabaix and Laibson, 2006[4]) or limited in cognitive ability (e.g., Spiegler, 2006; Piccione and Spiegler, 2012; Chioveanu and Zhou, 2014). In other cases, obfuscation effectively prevents (at least some) buyers from obtaining complete information in equilibrium by functioning as a search cost (e.g., Carlin, 2009; Ellison and Wolitzky, 2012). Notably, in many of these models, obfuscation is not only robust to competition, but actually *exacerbated* by it – firms increase efforts to obfuscate as the number of competitors in the market increases.

On the empirical side, some of the earliest work on price obfuscation comes from Morwitz, Greenleaf, and Johnson (1998), who coin the term "partitioned pricing."[5] In an auction

[2] *Phishing for Phools: The Economics of Manipulation and Deception* (165).

[3] Ellison (2006) and Grubb (2015) both provide fairly extensive surveys of key contributions in this literature.

[4] Gabaix and Laibson's work is by far the most well-known of these and has spawned a number of follow-on papers that extend the original model in various ways (e.g., Dahremoller, 2013; Wenzel (2014). It is also, perhaps, the most relevant here given its specific focus on shrouded surcharges. In this model, firms can choose whether or not to shroud high-priced add-ons (i.e., surcharges) – overdraft fees in retail banking, for example. The authors show that firms will shroud prices for avoidable (i.e., optional) add-ons if the proportion of myopic consumers in the population is large enough and will shroud unavoidable (i.e., mandatory) surcharges if there are *any* myopic consumers in the market!

[5] The practice of partitioning the total price of a good into two or more mandatory components (a surcharge – shrouded or not – is one example of partitioned pricing).

experiment with a buyer's premium assigned to the treatment group, these authors find that partitioned pricing significantly increases effective demand, and present preliminary evidence (from a second experiment) that this effect is due to consumers not assigning full weight to surcharges in their calculations of the total price of a good. This paper motivated a number of related studies (e.g., Lee and Han, 2002; Xia and Monroe, 2004) that subsequently confirmed this result.[6] Similarly, Hossain and Morgan (2006) find that high shipping charges increase total revenues in eBay auctions. Brown, Hossain, and Morgan (2010) refine this result, finding that eBay sellers can capture increased revenue by raising shipping charges when these charges are *shrouded*, but not when they are clearly disclosed. Ellison and Ellison (2009) examine obfuscation on PriceWatch, an online price search engine for firms selling computer parts. They find that despite the fact that buyers are enormously price sensitive (the authors estimate elasticities of -20 or more for certain products), obfuscation is highly effective at raising markups – from an expected 3-6% to roughly 12%.

In summary, then, there is a strong theoretical case to be made for why price obfuscation *should* exist in equilibrium. Moreover, both experimental and observational evidence confirms that obfuscation seems to be a highly profitable strategy in many instances. Taking all this into consideration, perhaps the most relevant question going forward is not "how can we explain the *existence* of obfuscation," but rather: "why aren't *more* firms doing it?!"

2.2.2 So Why *Not* Obfuscate?

> *"Great firms, with a reputation which they have received from the past, and which they wish to transmit to the future, cannot be guilty of small frauds. They live by a continuity of trade, which detected fraud would spoil."*
>
> \- Walter Bagehot (1873)[7]

One potential explanation for the lack of more rampant price obfuscation is that it is costly, not logistically feasible, or simply illegal in some circumstances. But this explanation

[6] See Ahmetoglu et al. (2014) for a review of this body of literature.

[7] *Lombard Street: A Description of the Money Market (I.8).*

fails to account for why obfuscation is not more prevalent in many industries (including the hotel industry – the focus of this paper), where these practices are legal, free, and logistically straightforward. Another explanation is that consumers eventually learn to look out for hidden fees and factor them into their consumption decisions accordingly, leaving firms with no incentive to obfuscate. Again, however, there are many settings where this explanation does not suffice – numerous forces counteract such consumer learning effects, e.g., the entry of new myopic consumers to the market and the ability for firms to constantly introduce new shrouding techniques (Gabaix and Laibson, 2006).

An alternative (though not mutually exclusive) explanation involves a very simple assumption: obfuscation embitters consumers. Or, put more formally, consumers dislike transacting with firms that they view as deceptive, and may even expend effort to retaliate against them. If this is the case, then there are at least two sets of circumstances in which firms may have an incentive to avoid obfuscation: 1) If transactions between consumers and firms are repeated, and fees anger consumers enough that at least some take their business elsewhere in future periods, or 2) When demand depends on seller reputation and consumers can rate interactions with firms (e.g., via mechanisms such as Yelp or TripAdvisor). In this case, if consumers punish firms for obfuscation via lower ratings *ex post*, then firms may have an incentive to avoid obfuscation even if interactions are not repeated and the set of buyers in the market is different each period.

These ideas are certainly not new or foreign to managers, who have long expressed concerns that obfuscation may be detrimental to firms via reputational damage.[8] They are also not new to academics: the literature on relational contracts formalizes the notion that honesty in transactions can be enforced with the prospect of repeat business (e.g., Tesler, 1980; Klein and Leffler, 1981; MacLeod, 2007). Heyes and Kapur (2012) develop a model particularly relevant to the empirical setting in this paper: anger over a bad experience motivates consumers to switch products and/or share their negative experience online, and the threat of this response incentivizes good behavior on the part of the seller. In the context

[8]For an example of this insight in the hotel industry specifically, see Mogelonsky (2012).

of price obfuscation specifically, Ian Ayres and Barry Nalebuff articulate this precise idea in their 2003 article, "In Praise of Honest Pricing." A 2006 Boston Globe piece quotes Nalebuff reiterating a key message of this essay: "In the end, you don't fool the customers with the hidden price . . . and if they feel ripped off, they won't come back."[9] This claim is intuitive, but the empirical evidence around it is surprisingly scant (and much of the work that does exist relies on survey data[10]). Below, I highlight some important related contributions.

For obfuscation to be even partially deterred by reputational mechanisms, consumers must somehow punish firms for this behavior. Several papers support the plausibility of this notion, particularly if consumers perceive obfuscation tactics as explicitly unfair or deceptive. Kahneman, Knetsch, and Thaler (1986), for example, argue that consumer perceptions of price "fairness" vary greatly depending on the corresponding circumstances,[11] and, importantly, that *firms are constrained by these perceptions*. Lee and Han (2002) expose subjects in an experiment to both a good priced with a shrouded surcharge and a good with an "all-inclusive" price; the shrouded surcharge resulted in negative attitudes towards the associated brand. Similarly, Xia and Monroe (2004) find that while hidden surcharges do increase seller revenue, they may also produce a negative effect on consumers' perceived value. More generally, Roman (2010) finds that perceived deception[12] on the part of the seller has a strong negative influence on consumers' transactional satisfaction.

Alternatively, we might think of the incentives to avoid obfuscation not in terms of

[9]Shea (2006). Laibson's response in the same article: "Companies that hide fees may lose some customers, but along the way it's a good ride."

[10]Smith and Brynjolfsson (2001) is an interesting exception. In an Internet shopbot, these authors find that consumers are actually twice as sensitive to changes in shipping price as they are to changes in item price and propose a perception of "unfairness" regarding shipping charges as one potential explanation. They do stipulate, however, that this anomaly may simply be driven by the restrictiveness of the multinomial logic specification used to obtain their results.

[11]For example, most respondents believe it is fair for firms to raise prices if input costs increase, but not if demand experiences a short-term spike (e.g., demand for snow shovels the morning after a snowstorm).

[12]Roman defines deception broadly: "Deception comes in a wide array of forms other than the outright lie, and among the features that differentiate them are amount and sufficiency of information, degree of truthfulness, clarity, relevance, and intent."

punishment for deception but rather in terms of reward for honesty. The CSR literature touches on this idea, at least peripherally. The primary focus of this field has been to explore the relationship between "socially responsible behavior"[13] and firm performance. Perhaps surprisingly, there has been relatively little work on honesty/fairness as socially responsible behavior in and of itself. Instead, the literature has focused on the way in which a reputation for honesty and fairness may function as a mediating attribute through which firms are rewarded for socially responsible behavior (e.g., McWilliams and Siegel, 2001). In the context of pricing specifically, Matute-Vallejo et al. (2011) find that consumer beliefs about a firm's commitment to CSR positively influence perceptions of price fairness – which subsequently have a positive effect on consumers' feelings of satisfaction, commitment, and intentions of loyalty towards the firm in question. A brief but highly pertinent contribution also comes from O'Connor and Meister (2008), who seek to determine which CSR attributes consumers value most. Here, the authors have survey participants rank six statements by their respective importance; on average, consumers responded that a corporation's commitment to "be honest" ranked highest.

The literature detailed in this and the preceding sub-section thus motivates the following key hypothesis to be tested empirically:

Hypothesis 3 (H3): *The adoption of a hidden resort fee (i.e., price obfuscation) negatively impacts firm reputation in the form of lower subsequent traveler ratings.*

An additional goal of this paper is to shed light on how this effect may vary depending on various firm and market factors. If notions of "unfairness" drive punishment, then we might expect the negative impact on ratings to be larger in circumstances where resort fees seem less fair (e.g., at low-quality hotels and/or hotels that do not provide any of the amenities traditionally associated with a "resort").[14] If shrouded surcharges affect perceived

[13] E.g., philanthropy, environmentally friendly business practices, etc.

[14] This potential mechanism seems particularly relevant given findings from Bertini and Mathieu (2008), who note that a "partitioned price increases the amount of attention paid to secondary attributes tagged with

value as in Xia and Monroe (2004), then punishment might be more severe in more price-sensitive segments of the market. Empirically, differentiating between these two mechanisms is difficult, since prices and quality are inherently correlated. Results from Heo and Lee (2011) further complicate the issue: these authors study perceptions of fairness in the hotel industry specifically, and find that price-conscious customers are also more likely to view opportunistic pricing strategies as unfair.

Definitively untangling the specific mechanism that might spur consumers to punish firms for obfuscation is beyond the scope of this paper. If the mechanism is an issue of either fairness or value, however, it will manifest in the data in essentially the same way: lower-quality, lower-priced firms will be punished more severely. This leads to a secondary hypothesis:

Hypothesis 4 (H4): *The negative impact on ratings will be larger in magnitude at lower-quality / lower-priced hotels.*

2.2.3 Ratings, Reputation, and Firm Performance

Ratings are the key outcome variable studied in this paper. Online feedback mechanisms provide a forum for consumers to share information about the quality of products and experiences, and potential buyers often rely heavily on ratings when making purchase decisions.[15] Indeed, online ratings are supplanting more "traditional" forms of reputation in many instances. Luca (2011), for example, finds that the market share for restaurants with chain-affiliation has decreased as Yelp penetration has increased – suggesting that online ratings may act as a substitute for brand-based reputation.

In the management and economics literature, reputation has been well established as an important source of competitive advantage, as favorable reputations may enable firms to

distinct price components." In other words, if surcharges are dubbed "resort fees" (as they are in almost all cases here), then this may increase consumers' scrutiny of corresponding "resort amenities" (or lack thereof).

[15] See Dellarocas (2003) or Josang, Ismail, and Boyd (2006) for a more comprehensive review of the literature on online feedback mechanisms.

charge premium prices, inhibit the mobility of rivals, attract superior employees, gain access to capital/investors, and sustain superior profit outcomes over time (e.g., Fombrun and Shanley, 1990; Roberts and Dowling, 2002). In online settings in particular, seller reputation in the form of ratings has been shown to have a substantial impact on demand. Several authors have studied this in the context of eBay, where there have been at least nine papers since 2001 (see Cabral and Hortacsu (2010) for details) documenting a positive correlation between seller reputation and sale prices, number of bids, and/or probability of sale in cross-sectional data. Resnick, Zeckhauser, Swanson and Lockwood (2006) conduct a field experiment (in an attempt to address endogeneity issues inherent in cross-sectional analysis) and find that there is a significant premium to having a large *number* of positive reviews – in other words, a well-established reputation is valuable. Cabral and Hortacsu (2010) utilize panel data to study the impact of ratings as they evolve over time; these authors find that weekly sales drop substantially after a seller receives her first negative feedback and that exit becomes more likely as average ratings fall.

Outside the eBay setting, Luca (2011) uses a regression discontinuity design to study the relationship between Yelp ratings and restaurant revenue, concluding that a one-star increase on Yelp results in a 5-9% increase in sales (with the effect driven primarily by independent restaurants). And in the hotel industry, the setting for this paper, ratings play a critical role: an eMarketer study from March 2015 reports that 81% of consumers find reviews "important" when making booking decisions, and 49% would not book a property that did not have any reviews. Using transactional data from an online travel agency, Anderson (2012) finds that if a hotel increases its review score by 1 point (on a 5-point scale), then it can increase its price by 11.2% and still maintain the same occupancy. Similarly, Expedia (2012) reports that a 1-point increase in review scores equates to a 9% increase in average daily room rates. While there is some concern about the degree to which we can interpret these last two findings as causal, that they are on the same order of magnitude as Luca (2011) lends some confidence to their general validity.

2.3 Empirical Context and Data

For general background on shrouded surcharges in the U.S. hotel industry, please see Section 1.3, which outlines basic information on both mandatory and avoidable fees. Here, I focus specifically on the most common type of mandatory surcharge: resort fees. Roughly 6.8% of hotels in my dataset charge these fees,[16] which are typically not disclosed until later in the booking process – often after the consumer has provided all necessary booking information, and even then, often only in fine print.[17]

Figure 2.1 outlines a timeline of the steps that occur in a typical transaction between customer and hotel. Because payment is generally not due at the time of booking but rather at the time of *departure* from the hotel, many buyers may not notice resort fee surcharges when making their purchase decision. And even if buyers are aware of the fees at the time of booking, it is likely that many do not fully account for them until payment is actually due (as in Morwitz, Greenleaf, and Johnson (1998), where consumers fail to fully account for partitioned surcharges). News coverage and anecdotal evidence from traveler reviews suggest that consumers are often, indeed, both surprised and angry about resort fees upon the receipt of their final bill.

2.3.1 Expedia and the OTA Channel

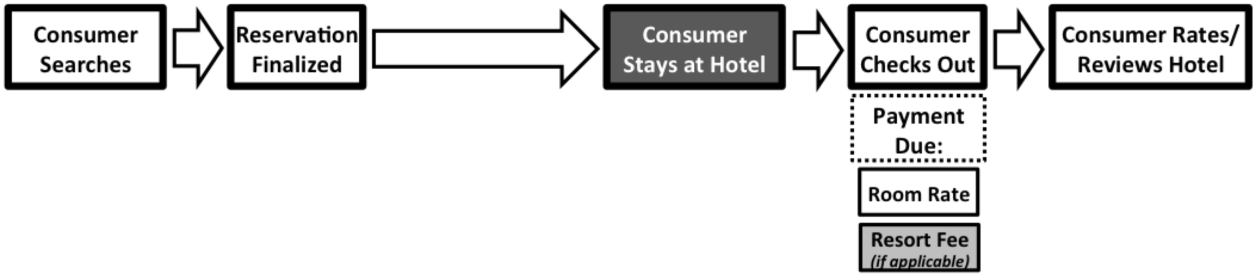
Like Chapter 1, this chapter utilizes data on U.S. hotels collected from a major online travel agency (OTA), Hotels.com (a subsidiary brand of Expedia).[18] In the U.S., 15-16% of

[16]The American Hotel & Lodging Association reports a similar figure of 7%.

[17]This is true for the vast majority of bookings made via all major channels.

[18]Throughout the remainder of the text, I refer to the entities "Hotels.com" and "Expedia" interchangeably. As a practical manner, the informational content that is relevant for this analysis is equivalent across Hotels.com and Expedia.com (Expedia's two largest hotel booking platforms). Most importantly, the presentation/handling of pricing and payments (including resort fees) is the same, and traveler reviews are pooled across the two sites (i.e., reviews from Expedia.com are included in the ratings/reviews listed on Hotels.com and are thus captured in my data). In this sense, the analysis presented here effectively applies to the segment of the market that books via either site.

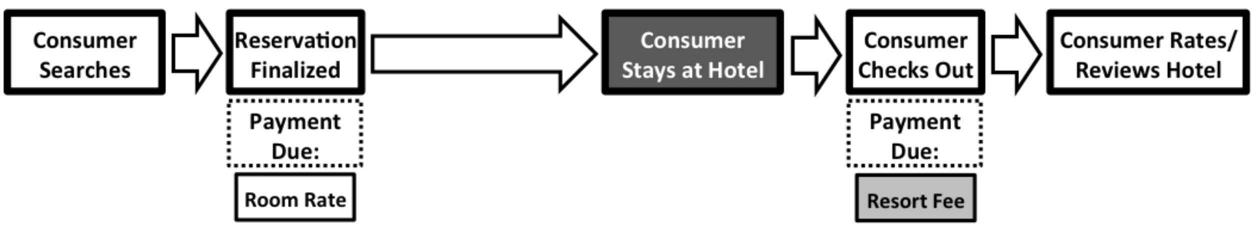
Figure 2.1: Timeline for a Typical (Non-Expedia) Hotel Transaction



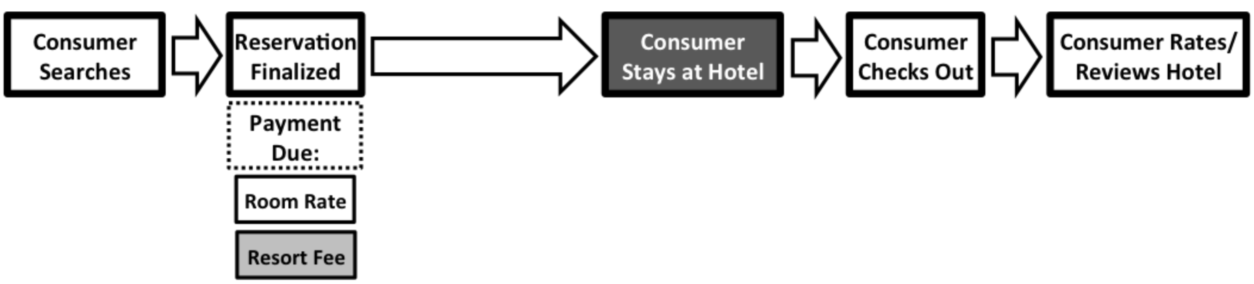
For travelers booking rooms via channels other than Expedia, payment is typically not due until the traveler departs the hotel. Because resort fees are often not clearly disclosed at the time of booking, travelers may not notice them (or not fully account for them) until payment is actually requested at the end of their stay.

Figure 2.2: Timelines for a Typical Expedia Hotel Transaction

(a) Resort Fees Charged Separately (*resort_fee_sep*=1)



(b) Resort Fees Included Up Front (*resort_fee_inc*=1



On Expedia, hotels that charge resort fees can choose to either include this fee in the total price charged up front (b) or to charge the fee separately to the traveler at the hotel (a). In the case of (a), consumers may not notice (or fully account for) the fee at the time of booking, in parallel with the situation depicted in Figure 2.1 above. In (b), however, there is no opportunity for consumers to be surprised by the fee, as it is (by definition) fully disclosed when its payment is required at the time of booking.

individual consumer hotel bookings are conducted through OTAs (see Table A5), which are web-based platforms that allow travelers to search for, compare, and reserve travel-related goods such as hotels, airfare, and rentals cars. In addition to Hotels.com, Expedia's brands include Expedia.com, Hotwire, Travelocity, and Orbitz. As of year-end 2015, these platforms accounted for roughly 8% of total hotel bookings in the U.S. (equivalent to a 50-60% share of the U.S. OTA market), with Hotels.com representing the largest portion.[19]

Expedia and its subsidiary brands conduct the majority of their hotel bookings via a "pay now" merchant model: Expedia contracts with hotels to sell blocks of inventory, and travelers pay for these bookings *up front* directly through the OTA website, with Expedia as the merchant of record.[20] In contrast, major OTA competitors such as Booking.com primarily utilize an agency model in which travelers book rooms via the OTA but do not pay until they arrive at the hotel property – a process that more closely resembles the way in which the majority of bookings occur outside the OTA channel (where payment is typically not due until check-out at the end of the hotel stay). This distinction will become important in Section 2.5, as it has implications for the way in which resort fees are presented to (and processed by) consumers on Expedia versus other booking channels.

From the perspective of the researcher, the Hotels.com website is an excellent source of data on U.S. hotels. The website includes listings for more than 50,000 individual properties,[21] reflecting upwards of 90% coverage of the roughly 53,000 hotels in the U.S.[22] For the majority of these hotels, Hotels.com provides data on average cumulative traveler ratings, room

[19] Expedia Q4 2015 investor presentation (February 10, 2016).

[20] Prior to 2012, *all* of Expedia's hotel bookings were conducted via the merchant model. In 2012, Expedia also introduced a "pay later" (agency model) option. As of 2015, an Expedia market manager reported that roughly 40% of U.S. hotels were enrolled in both the merchant model and the agency model, while roughly 60% continued to utilize only the merchant model. Of the 40% that provided both payment options, approximately 60% of bookings continued to flow through the "pay now" merchant model. This split suggests that roughly 80% of total hotel bookings on Expedia were conducted via the merchant model as of 2015.

[21] This figure reflects coverage as of March 2016. Hotels.com coverage was less expansive at the beginning of my data collection efforts in April 2015, at approximately 45,000 U.S. hotels.

[22] Per the American Hotel and Lodging Association as of 2015.

rates, mandatory fees, fees for optional add-ons (Wi-Fi, parking, etc.), and a wide range of hotel characteristics. Monthly cross-sectional snapshots of this data captured between April 2015 and March 2016 allow me to observe variation in hotel resort fee policies (and other characteristics) over time.

In addition to the information described above, Hotels.com also provides reviews from individual travelers for most hotel properties. Each review contains the date of the traveler's stay, the date that the review was written, a rating between 1 and 5, (optional) written commentary from the reviewer, and, in some cases, information about the traveler's location of origin and reason for travel. Importantly, to write a review on an Expedia-brand site, a traveler *must have verifiably booked through the Expedia platform.* This feature of the data (in combination with the fact that resort fees are handled differently on Expedia versus other booking channels for at least a subset of hotels) will facilitate identification in the difference-in-differences analysis presented in Section 2.5.

2.3.2 TripAdvisor

In Section 2.5's difference-in-differences analysis, I also utilize individual traveler review data from TripAdvisor. Unlike Hotels.com, TripAdvisor is not an OTA in the traditional sense.[23] Instead, it is a web-based aggregator of ratings for travel-related goods – hotels, attractions, and even restaurants. Travelers use TripAdvisor primarily to conduct research when planning trips and to rate their experiences afterwards. The site is massive, providing reviews for nearly one million hotels worldwide.[24]

The basic information contained in each individual TripAdvisor review largely mirrors that described for Expedia reviews above. A critical difference, however, is the ability for *anyone* to write a review on TripAdvisor. In empirical analyses, I thus use TripAdvisor

---

[23]TripAdvisor has begun to move in this direction, adding an "instant booking" feature in 2014. To date, however, this line of business constitutes only a small portion of TripAdvisor's revenue, which comes largely from advertisements.

[24]Per TripAdvisor 2015 10-K filings.

reviewers as a proxy for non-Expedia purchasers. It is important to note, however, that there are, presumably, some Expedia buyers who write reviews on TripAdvisor, since the site is open to anyone. While the ideal dataset would guarantee mutual exclusivity between these two groups, the overlap here is not likely to be problematic in practice for two reasons. Firstly, having some control group observations (reviews from Expedia buyers) mixed in with the treatment group (reviews from non-Expedia buyers, proxied by TripAdvisor reviews) has the effect of biasing the estimated treatment effect towards zero in the difference-in-differences model specified here. So if anything, the treatment effect I estimate will be conservative in magnitude as a result of this issue. Secondly, the proportion of TripAdvisor reviewers that are Expedia buyers is likely to be relatively small, as Expedia brands account for only 8% of total U.S. bookings. Moreover, Expedia buyers receive email prompts to review their stay *on Expedia*, so they are arguably more likely to do so than they are to write a review on TripAdvisor. In practice, the percent of TripAdvisor reviews in my data that explicitly mention "Expedia" or "Hotels.com" in their review text is 0.5%.

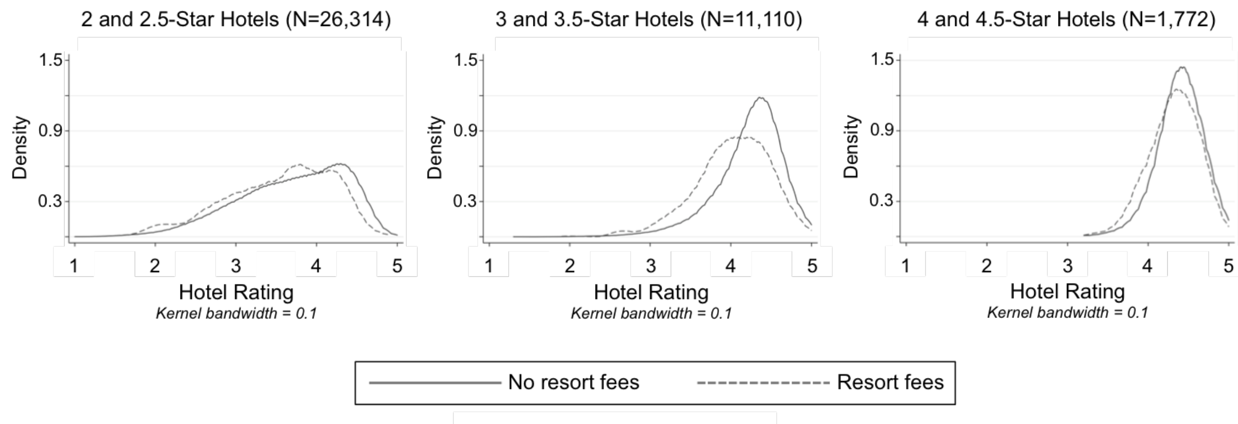
2.4 Resort Fees and Ratings: A Cross-Sectional Snapshot

While the crux of this paper's empirical analysis focuses on what happens to traveler ratings at hotels where the resort fee policy *changes* over time, it is useful to begin by first examining a static cross-section of the overall U.S. hotel market for context.[25] Figure 2.3 illustrates a strong negative relationship between resort fees and cumulative average traveler ratings: of all U.S. hotels listed on Expedia, those that charge resort fees have lower average ratings in each major star category.[26]

[25] All figures, summary statistics, and cross-sectional analyses presented here are based on a cross-section of data collected in July 2015. Any of the 12 cross-sections collected between April 2015 and March 2016, however, yield substantively similar empirical findings.

[26] See Table A2 for more information on star categorizations. 97% of hotels in the sample fall between 2 and 4.5 stars and are thus captured in one of the three major star categories illustrated. For the remaining 1,531 hotels at the very low end (1-star and 1.5-star) and very high end (5-star), a t-test does not reject the null hypothesis that the means for the resort fee vs. non-resort fee groups are the same.

Figure 2.3: Cross-Sectional Rating Densities for Hotels With vs. Without Resort Fees



Data reflects cross-sectional cumulative average ratings for hotels as of July 2015.

Of course there is ample reason for skepticism when interpreting these distributions – the decision to adopt resort fees is hardly exogenous. A natural question is whether or not hotels that charge resort fees differ systematically from those that do not. To shed light on this issue, I regress resort fee utilization (coded as a dummy variable equal to 0 or 1) on basic firm characteristics and market fixed effects.[27] Correlational results are presented in Table 2.1. Hotels that charge resort fees tend to be higher-end, and, perhaps unsurprisingly, tend to feature traditional "resort" amenities such as spas, health clubs, and golf courses.[28] These establishments are also *less* likely to be affiliated with major chains – an important observation, since chain affiliation is correlated with higher ratings (see Table 2.3). That the coefficient on price[29] is not statistically different from zero indicates that hotels charging resort fees tend to have base prices that are similar to their competitors, after accounting for star category, amenities, and location (i.e., market). In other words, these hotels will appear comparable to competitors in price during search, but are actually more expensive once hidden resort fees are factored in. Finally, the introduction of market-level fixed effects

[27]See Table A2 for detailed descriptions of right-hand-side variables.

[28]See table A7 for a detailed breakdown of resort fee utilization trends by star category.

[29]Note that in all cases throughout this paper, *price* and *log_price* reflect base prices – i.e., the price before resort fees are added on.

raises the R-squared in this specification substantially (from roughly 0.1 to 0.2), indicating the likely importance of location. Table A6 underscores this notion, illustrating that resort fee utilization tends to be largely clustered in certain geographic areas.[30]

Table 2.1: What Firm Characteristics are Correlated with the Use of Resort Fees?

	OLS Estimates			
	Dependent Variable: Hotel's Use of Resort Fee (0 or 1)			
	(1)	(2)	(3)	(4)
stars	0.054 * **	0.052 * **	0.051 * **	0.045 * **
	(0.005)	(0.004)	(0.007)	(0.005)
resort_amenities	0.173 * **	0.154 * **	0.154 * **	0.119 * **
	(0.012)	(0.011)	(0.012)	(0.008)
major_chain		−0.080 * **	−0.081 * **	−0.061 * **
		(0.005)	(0.005)	(0.004)
log_price			0.001	−0.001
			(0.010)	(0.007)
Market Fixed Effects	No	No	No	MSA[a]
Observations	40,584	40,584	39,829	39,829
R-squared	0.09	0.12	0.12	0.22

Standard errors in parentheses reflect clustering at the ZIP-5 level

(8,891 clusters in Models 1 and 2 and 8,834 clusters in Models 3 and 4)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] *Metropolitan statistical area*

Note: See Table A2 for detailed information on right-hand-side variables.

[30] Chiles (2016) addresses the competitive market forces that potentially influence a firm's incentives to obfuscate. These issues are beyond the scope of this paper, and I abstract away from them with the use of market-level fixed effects in regression specifications.

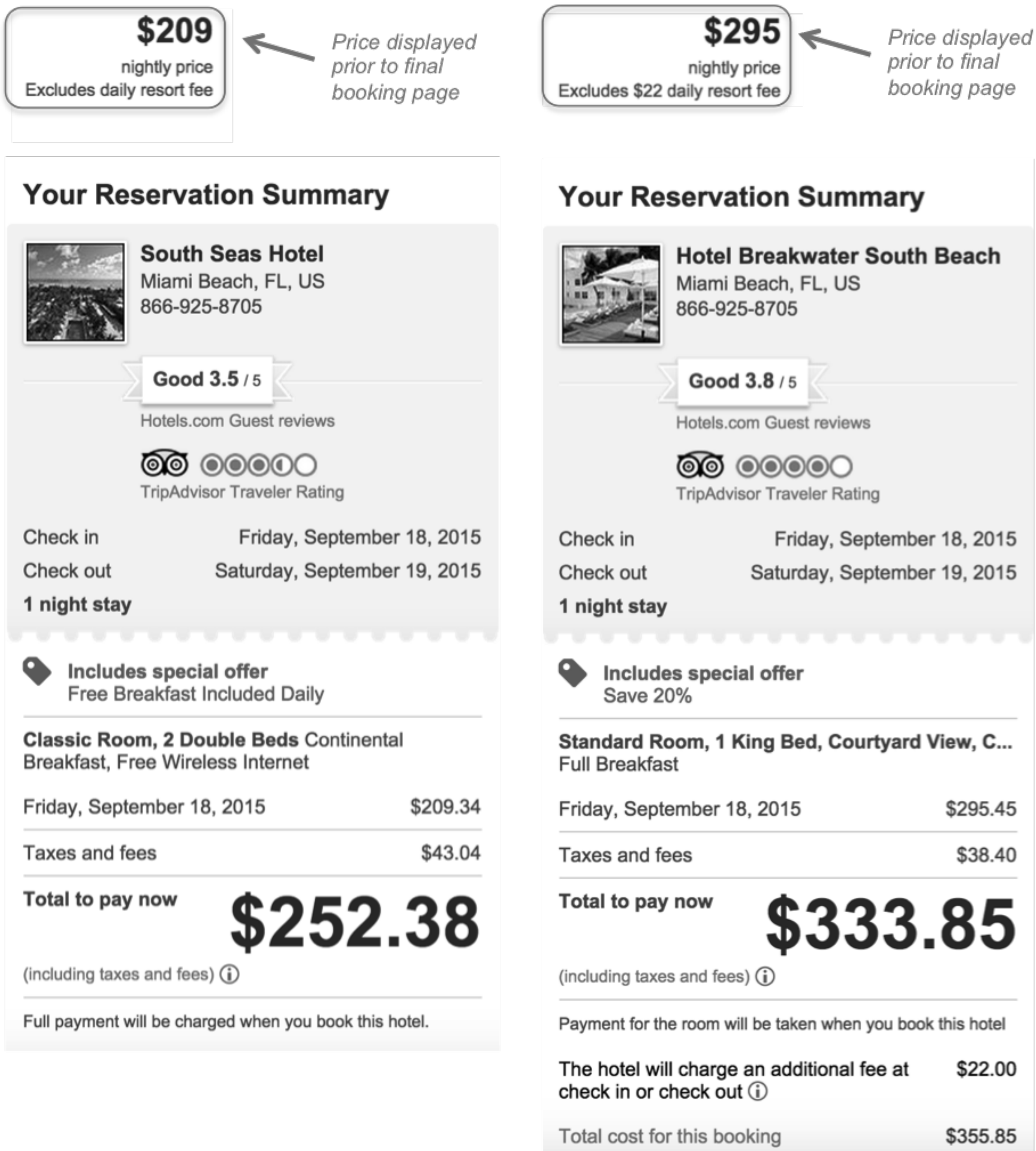
Clearly, then, there are important differences in hotels that adopt resort fees and hotels that do not. So does the negative correlation between ratings and fees (observed in Figure 2.3) persist after controlling for observable factors? To answer this question, it is necessary to first define variables that distinguish between the two distinct ways in which resort fees may be implemented on Expedia:

- ***resort_fee_shrouded:*** A dummy variable, equal to 1 if the hotel charges a resort fee that is *not* included in the total price paid up front by Hotels.com/Expedia customers (i.e., the fee is "separate").
- ***resort_fee_unshrouded:*** A dummy variable, equal to 1 if the hotel charges a resort fee that *is* included in the total price paid up front by Hotels.com/Expedia customers (i.e., the fee is "included"). Note that if a hotel does not charge a resort fee at all, both *resort_fee_shrouded* and *resort_fee_unshrouded* are equal to 0.

Recall from Section 2.3 that most customers who purchase hotel rooms on Expedia actually pay at the time of booking versus at the hotel. As such, hotels that charge a resort fee may choose to have customers pay Expedia the fee up front along with the room rate (the fee is "included" or "unshrouded"), or, alternatively, to wait until the customer arrives at the property to charge them the fee directly (the fee is "separate" or "shrouded"). Figure 2.2 provides an illustration of these respective transactional timelines, and Figure 2.4 provides a comparison of the screens that consumers encounter in each of these cases.[31] As Figure 2.4 illustrates, "separate" fees are shrouded in fine print on Expedia at the time of booking, and since customers are not asked to pay them up front, they are easy to miss. In contrast, "included" fees are, at least for buyers on Expedia, *not hidden* at the time of booking, since the total price (inclusive of fees) is both presented and charged up front. This practice – actually requiring payment of the resort fee at the time of booking – effectively unshrouds the fee and is almost entirely unique to the Expedia booking channel.

[31] To understand the incentives a hotel faces when determining which resort fee payment structure to select, recall that Expedia makes money by taking a percentage of the booking value. Thus, on the one hand, the incentive for a hotel *not* to include the resort fee in the amount paid up front is obvious: firms are not charged a commission on the fee if it is collected at the property versus through the Expedia interface. On the other hand, trying to collect the fee once a guest arrives may be more of a logistical hassle for firms. Ultimately this decision is at the discretion of the revenue manager at each individual property, and, like the decision to charge a resort fee in the first place, it may be correlated with other factors that affect ratings.

Figure 2.4: "Included" vs. "Separate" Resort Fees on Hotels.com



The South Seas Hotel and the Hotel Breakwater – both 3.5 star hotels in Miami – collect payment for resort fees differently on the Expedia platform. On the left, the total price ***includes*** *a resort fee of \$15 (embedded within the "taxes and fees" line). On the right, total price does* ***not*** *include a resort fee of \$22.00, which is instead collected at the property (as noted in fine print at the bottom of the page).*

Returning to the relationship between fees and ratings observed in Figure 2.3, Table 2.4 presents results for various specifications of the following model, where X_j is a vector of firm and market characteristics corresponding to hotel j:

$$avg\_rating_j = \beta_0 + \beta_1(resort\_fee\_sep_j) + \beta_2(resort\_fee\_inc_j) + \alpha' X_j + \varepsilon_j \tag{2.1}$$

Summary statistics and detailed variable descriptions can be found in Tables 2.2, 2.3, A2, A3, A4, and A7.[32]

Table 2.2: Summary Statistics for Key Firm-Level Variables

Variable	**Obs**	**Mean**	**St. Dev.**	**Min**	**Max**
avg_rating	40,586	3.836	0.678	1	5
resort_fee_sep	40,586	0.043	0.203	0	1
resort_fee_inc	40,586	0.024	0.154	0	1
stars	40,586	2.549	0.616	1	5
resort_amenities	40,586	0.167	0.373	0	1
price	39,830	108.854	64.090	10	1,750
rooms	35,630	113.851	154.468	1	5,000
major_chain	40,586	0.641	0.480	0	1
optional_fees	40,586	0.244	0.511	0	4

Table 2.3: Correlation Matrix for Key Firm-Level Variables

	avg_rating	resort_fee_sep	resort_fee_inc	stars	resort_amenities	major_chain	log_price	log_rooms	optional_fees
avg_rating	1.000								
resort_fee_sep	0.027*	1.000							
resort_fee_inc	0.013*	−0.034*	1.000						
stars	0.551*	0.211*	0.078*	1.000					
resort_amenities	0.136*	0.252*	0.143*	0.350*	1.000				
major_chain	0.143*	−0.171*	−0.115*	−0.093*	−0.186*	1.000			
log_price	0.565*	0.136*	0.083*	0.643*	0.304*	−0.114*	1.000		
log_rooms	0.069*	0.127*	0.001	0.342*	0.155*	0.312*	0.105*	1.000	
optional_fees	−0.001	0.056*	0.061*	0.230*	0.154*	−0.050*	0.128*	0.218*	1.000

* $p < 0.01$

[32] Note that roughly 11% of the 46,329 U.S. hotels listed on Expedia/Hotels.com (as of July 2015) lack either star categorizations or information on average traveler ratings, and thus must be excluded from the analyses presented here. The majority of this loss is due to the fact that some hotels simply have no traveler reviews.

Table 2.4: Cross-Sectional OLS Results

	Dependent Variable: Average (Cumulative) Hotel Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
resort_fee_shrouded	−0.36***	−0.05**	−0.07***	−0.06***	−0.07***	−0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
resort_fee_unshrouded	−0.16***	−0.01	−0.03*	−0.03*	−0.03*	−0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
stars	0.63***	0.48***	0.47***	0.43***	0.43***	0.39***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log_price		0.32***	0.32***	0.48***	0.48***	0.54***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
log_rooms		−0.15***	−0.19***	−0.16***	−0.16***	−0.12***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
optional_fees					−0.02***	−0.01
					(0.00)	(0.01)
Chain Fixed Effects[a]	No	Yes	Yes	Yes	Yes	Yes
Detailed Firm Controls[a]	No	No	Yes	Yes	Yes	Yes
Market Fixed Effects	No	No	No	MSA	MSA	ZIP-5
Constant	2.24***	1.55***	1.68***	0.96***	0.96***	0.64***
	(0.02)	(0.05)	(0.06)	(0.11)	(0.11)	(0.09)
Observations	40,584	35,075	35,075	35,075	35,075	35,075
R-squared	0.31	0.59	0.60	0.64	0.64	0.75

Standard errors in parentheses reflect clustering at the ZIP-5 level
(8,891 clusters in Model 1 and 8,271 clusters in Models 2-6)
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] *See Tables A3 and A4 in the Appendix for details.*

The first notable result here is that the coefficient on *resort_fee_unshrouded* is insignificant after basic controls are added to the model. This is in line with the narrative that there is a "hidden fee effect" driving the negative relationship between ratings and fees rather than some unobserved factor – since fees are not actually hidden from Expedia buyers when the fee is "included," it is not surprising that we see no negative impact on ratings in this case. An equally important result is that the coefficient on *resort_fee_shrouded* is robustly negative and significant. The magnitude of the estimate does fall substantially with the addition of chain fixed effects to the model, but this is not unexpected given the correlations between fees, chain-affiliation, and ratings (see Table 2.3). What *is*, perhaps, surprising is how stable the coefficient estimate on *resort_fee_shrouded* remains as additional firm and market-level controls are added in Models (2) through (6). Though the effect is small (a difference of between .05 and .10 points on a rating scale that ranges from 1 to 5), these results add credence to the hypothesis that hidden fees may be negatively impacting traveler ratings.[33]

2.5 Hidden Fees and Ratings: Estimating the Relationship

While the cross-sectional evidence is clearly suggestive, it is not sufficient to conclude that there is a causal relationship between hidden fees and firm reputation. To identify such an effect, I focus on trends in individual traveler ratings at hotel properties where resort fee policies *change*. As noted in Section 2.3, repeated cross-sectional datasets captured monthly between April 2015 and March 2016 allow me to observe variation in hotel resort fee policies (and other characteristics) over time. Table 2.5 provides a summary of the changes in resort fee policy that occurred over this period.

Table 2.5: Resort Fee Policy Changes (April 2015 - March 2016)

	Resort Fee Is:		
	Separate	*Included*	**Total Hotels**
Adopted	249	132	**381**
	182	*104*	***286***
Dropped	106	84	**190**
	66	*67*	***133***
Total	**355**	**216**	**571**
	248	***171***	***419***

Numbers in italics indicate the number of hotels in each category that are actually eligible for inclusion in the Section 2.5 (D-in-D) analysis, while top-line figures indicate the total number of hotels undergoing policy changes.

In line with news coverage, the prevalence of resort fees is, on net, increasing: 381 U.S.

[33] In additional specifications (see Table A9), I explore whether or not the magnitude of the fee (either in dollars or as a percentage of room rate) makes a difference in the effect on ratings. Conditional on charging a resort fee, the size of the fee does not seem to matter at all! At first take, this finding is somewhat surprising. Perhaps, though, it is in line with the view that consumers are irritated about resort fees not because they have to pay more (which would make magnitude important), but rather because they feel duped (in which case it's the *principle* of the fee that upsets them, not the amount).

hotels adopted resort fees during the sample window, while 190 discontinued the use of these surcharges.[34] For the 571 hotels that either added or dropped resort fees, I merge the panel of information on hotel characteristics described above with individual traveler review data from both Expedia and TripAdvisor. Since information on the date of the traveler's stay is provided in the review data, I can deduce whether or not resort fees were in effect at the time an individual reviewer stayed at the hotel property in question.

For each hotel, I focus on reviews from the twelve months leading up to the policy change plus those from the three months following the policy change. Of the original 571 hotels, 419 have at least one review both pre- and post-policy change from both Expedia and TripAdvisor (the minimum required for inclusion in the Section 2.5 analysis).[35] This set of 419 hotels corresponds to a sample of 120,498 individual traveler reviews (an average of 288 reviews per hotel).[36]

In addition to the firm-level variables collected from Expedia (detailed in Tables A2 and A3), there are a few key review-level variables that must be defined. Tables 2.6 and A10 provide summary statistics for the following:

- ***rating:*** Individual traveler rating for a hotel, provided as an integer value between 1 and 5. (It is important to distinguish between *rating* and *average_rating*, the variable utilized in the preceding cross-sectional analysis.) Recall that all ratings on Expedia sites are submitted *only* by travelers who book on Expedia, whereas TripAdvisor ratings may be submitted by anyone, regardless of how they have booked their room.
- ***tripadv:*** A dummy variable, equal to 1 if the review/rating comes from TripAdvisor,

[34] In addition to hotels that adopt resort fees and drop resort fees, there are also some hotels that appear to make multiple changes over the course of the sample window (e.g., adopt a fee, then delete it, then adopt it again). This is not common, however, and I do not include these hotels in the analysis here (partly out of concerns for the integrity of the data when unusual changes like this appear to occur, and partly out of a desire to keep the empirical analysis straightforward and intuitive for readers. The inclusion of these hotels in the analysis does not substantively change any results.

[35] There are several reasons why a hotel might have a very small number of reviews. The most obvious is that a hotel is small or relatively new. In the case where reviews cease past a certain point in time, it is possible that the hotel has actually been closed (although in most cases it seems that both Expedia and TripAdvisor have a general policy of de-listing the pages for properties that have closed, mitigating the likelihood of this possibility).

[36] 65,040 from Expedia and 55,458 from TripAdvisor.

and equal to 0 if the review/rating comes from Expedia. In the subsequent difference-in-differences analysis, this effectively serves as an indicator for whether or not a review comes from the "treatment group."

- ***trip_type:*** A categorical variable indicating the purpose/type of the reviewer's trip. Possible values include: "Business," "Family," "Friends," "Couple," and "Other/Unspecified."

- ***reviewer_usa:*** A dummy variable, equal to 1 if the reviewer is from the U.S.

Table 2.6: Summary Statistics for Key Review-Level Variables

	Reviews for "Included" Fee Hotels					**Reviews for "Separate" Fee Hotels**				
Variable	**Obs**	**Mean**	**SD**	**Min**	**Max**	**Obs**	**Mean**	**SD**	**Min**	**Max**
rating	42,876	3.95	1.15	1	5	77,622	3.99	1.14	1	5
tripadv	42,876	0.46	0.50	0	1	77,622	0.46	0.50	0	1
reviewer_usa	38,579	0.84	0.37	0	1	77,622	0.80	0.40	0	1

The preceding section discussed resort fee implementation on Expedia. For the purposes of the subsequent analysis, it is also important to establish how resort fees are presented *outside* the Expedia setting. In the case of both *resort_fee_shrouded=1* and *resort_fee_unshrouded=1*, resort fees are unlikely to be disclosed clearly for customers booking via channels other than Expedia. This is important for identification, as it allows me to exploit variation in resort fee disclosure when these fees are *not* shrouded on Expedia. Figure 2.5 illustrates an example of this disparity. Of the 2,608 hotels that charge resort fees in my dataset, I selected 100 at random and conducted manual checks for resort fee disclosure on the hotels' own websites.[37] Even on the final booking screen (when credit card information is required to hold the reservation), 68% disclosed the fee only in fine print, on a separate (hyperlinked) page or pop-up, or via a mouseover feature. In these cases, resort fees were not included in the grand-total dollar amount displayed to buyers (in parallel with the way that "separate" fees are displayed on Expedia).

The remaining 32% of hotels did display the fees either as an individual line item or as part of a "taxes and fees" line that ultimately rolled into an inclusive grand-total amount. For several reasons, however, it is arguable that this is not equivalent to the level of disclosure with

[37]These checks were conducted in May 2015.

Figure 2.5: Resort Fees ("Included") on Hotels.com vs. Elsewhere

The total price for the Fairmont Scottsdale is displayed differently depending on where a traveler books. On Hotels.com, the large-font total ***includes*** *the resort fee, while the Fairmont's own website only displays this additional charge in fine print.*

which "included" fees are handled on Expedia. For one, buyers outside the Expedia setting are not typically billed up front. In this situation, it seems far more likely that consumers might anchor onto an initially quoted base price and pay less attention to a fee-inclusive grand total that is not actually due at booking. In addition, the prominence of a final fee-inclusive total varied substantially across hotels. Some displayed it very conspicuously. In many cases, though, this figure was presented in a light font or in the far corner of the screen where it might easily be missed.

2.5.1 A Difference-in-Differences Model

Figure 2.6: Traveler Ratings Before and After Resort Fee Adoption

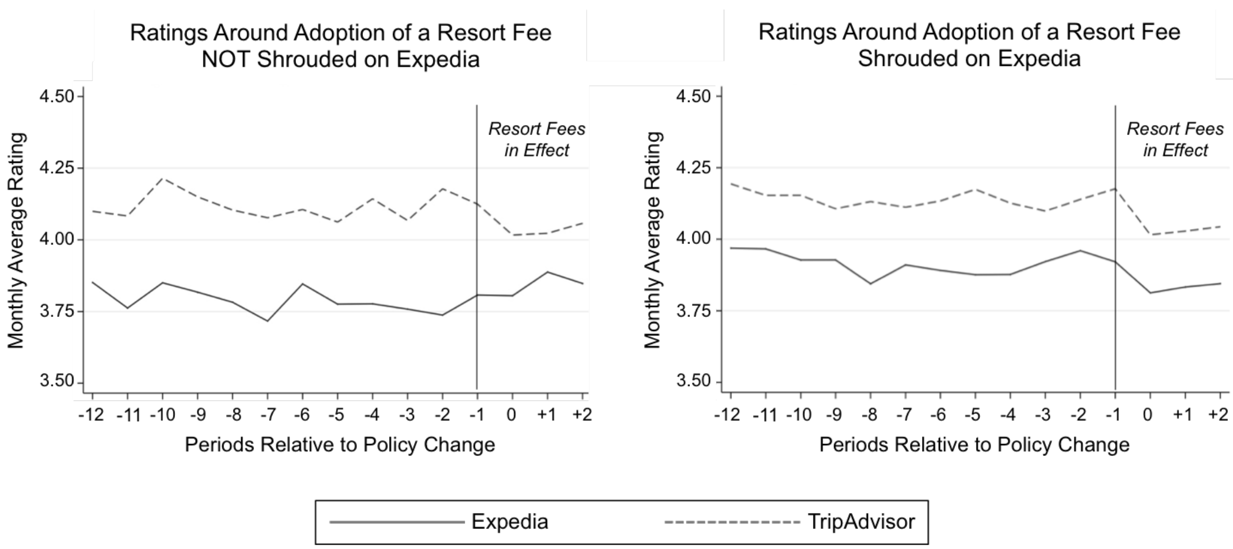


Figure 2.6 illustrates the intuition behind the difference-in-differences framework utilized here. On the right, we see ratings over time at both Expedia and TripAdvisor for the 182 hotels (66,197 corresponding reviews) that adopted "separate" resort fees.[38] In this case, when a hotel adopts a fee, we observe a negative effect on ratings in both groups of reviewers. This is in line our existing intuition. If the fee is "separate," then all travelers pay it at the hotel – it is shrouded from both Expedia reviewers and TripAdvisor reviewers at the time of booking, and both groups appear to punish firms via lower average ratings following adoption. Yet while this pattern is consistent with H1 (and with cross-sectional results), we cannot actually identify the effect of hidden fees on ratings in this scenario. Both groups of reviewers receive the hidden fee"treatment," so it is impossible to separate out the impact of hidden

[38]Note that these charts focus only on hotels that *adopt* fees for the sake of illustration purposes; the empirical analysis includes both hotels that adopt fees and hotels that drop fees.

fees from any other potential confounding factors that may be correlated with their adoption.

In the graph on the left, however, when the adopted resort fee is "included" (104 hotels and 25,513 corresponding reviews), ratings dip post-adoption at TripAdvisor but actually edge up a bit on Expedia. In this scenario, resort fees are *not actually hidden* from Expedia reviewers, allowing these reviewers to effectively function as a control group. The fact that ratings on Expedia do not fall following the adoption of a fee is thus not surprising (and, indeed, consistent with both H1 and cross-sectional results) – we do not expect to see any hidden fee effect in post-adoption ratings for this group. In contrast, travelers booking via non-Expedia channels *are* subject to the hidden fee "treatment," and any subsequent effect is reflected in lower ratings on TripAdvisor. This allows us to identify the effect of hidden fees on ratings: both sets of reviews absorb any potentially confounding factors associated with resort fee adoption, but only TripAdvisor reviews reflect the actual hidden fee effect.

I thus focus my analysis on the sub-sample of hotels[39] that make policy changes involving "included" resort fees, as it is only within this subset that we can actually identify the effect of hidden fees on ratings. Formally, I estimate the following model for traveler i's rating of firm j in period t:

$$rating_{ijt} = \beta_0 + \beta_1(resort\_fee_{jt}) + \beta_2(tripadv_{ijt}) + \beta_3(resort\_fee_{jt} * tripadv_{ijt}) + \varepsilon_{ijt} \qquad (2.2)$$

In the above specification, β_1 estimates the main effect of resort fees on ratings; this term absorbs fluctuations due to confounding factors that may be correlated with resort fee adoption and will be positive if hotel quality increases (on unobserved dimensions) in conjunction with the adoption of fees and negative if quality decreases. β_2 accounts for systematic differences in ratings from Expedia reviewers versus TripAdvisor reviewers (i.e., differences in the control group and treatment group). And β_3 is our treatment effect, measuring the causal effect of hidden fees on ratings (hypothesized in H1 to be negative). To increase the model's precision, I also include fixed effects and control variables in various specifications.

[39] 171 in total: 104 that adopted (illustrated in Figure 2.6) and 67 that dropped.

2.5.2 Key Empirical Results

Table 2.7 provides results for multiple specifications of the D-in-D model detailed above. A negative coefficient on the interaction term *tripadv * resort_fee* – the "hidden fee" treatment – supports H1. The adoption of a resort fee is associated with a fall in subsequent traveler ratings of roughly 0.15 points (or, conversely, the discontinuation of a resort fee is associated with an increase in ratings of this same magnitude). In practical terms, this means that TripAdvisor ratings fall roughly 0.15 points *more* than Expedia ratings when a hotel adopts a hidden resort fee of the "included" variety. This effect remains quite stable (and significant) as various controls are added to the model. (E.g., the introduction of firm fixed effects in Model (2) dramatically increases R-squared (from .01 to .21), but the coefficient estimate for our treatment effect is largely unchanged.)

One additional result here is that the main effect on *resort_fee* is actually positive, albeit marginally so (0.05 points). In other words, absent the "hidden fee effect," ratings actually rise a bit in conjunction with the adoption of a resort fee. How should this finding be interpreted? A comparison of hotel characteristics pre- vs. post-policy change helps to shed light on this issue. While hotel traits such as chain affiliation and amenities do not tend to change much over time at the vast majority of properties, there are some instances of churn. Table 2.8 details differences in average firm characteristics when resort fees are present versus when they are not.[40] Here we see that in almost every case, the adoption of resort fees is correlated with the provision of *more* amenities. In particular, resort fees seem to be correlated with the adoption of (relatively) easy-to-implement amenities such as concierge services and beach/pool amenities (e.g., cabanas, towel service, etc.). Resort fees are also marginally correlated with the provision of more capital-intensive amenities (e.g., pools, tennis/golf facilities), but these types of changes over time are substantially less common. In any case, all else equal, we would expect the provision of more amenities to contribute to higher ratings on average. And while all of the characteristics detailed in Table 2.8 are

[40] For the sake of clarity in diction, I describe these changes from the point of view of a hotel adopting a resort fee, but the reverse will be true for hotels dropping resort fees.

Table 2.7: Difference-In-Differences Estimation Results

	Dependent Variable: Traveler Rating				
	(1)	(2)	(3)	(4)	(5)
tripadv * resort_fee	−0.15 ***	−0.14 ***	−0.14 ***	−0.13 ***	−0.13 ***
	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
tripadv	0.32 ***	0.11 ***	0.10 ***	0.10 ***	0.04
	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
resort_fee	0.12 **	0.07 ***	0.06 **	0.05 **	0.04 **
	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)
Firm Fixed Effects	No	Yes	Yes	Yes	Yes
Month Fixed Effects	No	No	Yes	Yes	Yes
Chain Fixed Effects[a]	No	No	No	Yes	Yes
Firm Controls[b]	No	No	No	Yes	Yes
Traveler Controls[c]	No	No	No	No	Yes
Constant	3.78 ***	4.09 ***	4.06 ***	3.91 ***	3.87 ***
	(0.06)	(0.02)	(0.04)	(0.26)	(0.26)
Observations	42,876	42,876	42,876	42,082	37,879
R-squared	0.01	0.21	0.21	0.21	0.22

Standard errors in parentheses reflect clustering at the firm level
(171 clusters in Models 1-3 and 169 clusters in Models 4-5)
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] *These are allowed to vary over time. See Table A4 in the Appendix for details on chain fixed effects.*
[b] *These are allowed to vary over time, and include* ***stars***, ***log_price***, ***optional_fees***, *and all of the detailed controls listed in Table A3.*
[c] *These include* ***trip_type*** *and* ***reviewer_usa***.

observed and incorporated into Models (4) and (5), if hotels are also increasing quality on *unobserved* dimensions, then this may help to explain the positive coefficient estimate for *resort_fee*.

An implicit assumption of the D-in-D identification strategy utilized here is that the change in the control group post-treatment is an appropriate proxy for the counterfactual change that *would* have occurred in the treatment group had there been no treatment. Several arguments can be made for why this assumption seems reasonable in this setting. For one, ratings from Expedia and TripAdvisor appear to exhibit parallel (and roughly flat) trends prior to the resort fee "treatment" in the D-in-D sample (left half of Figure 2.6). To further examine the robustness of this observation, I estimate a model (for the subset of hotels that adopt fees) where *tripadv* (i.e., the indicator for whether or not a review comes from the

Table 2.8: Hotel Characteristics By Resort Fee Regime

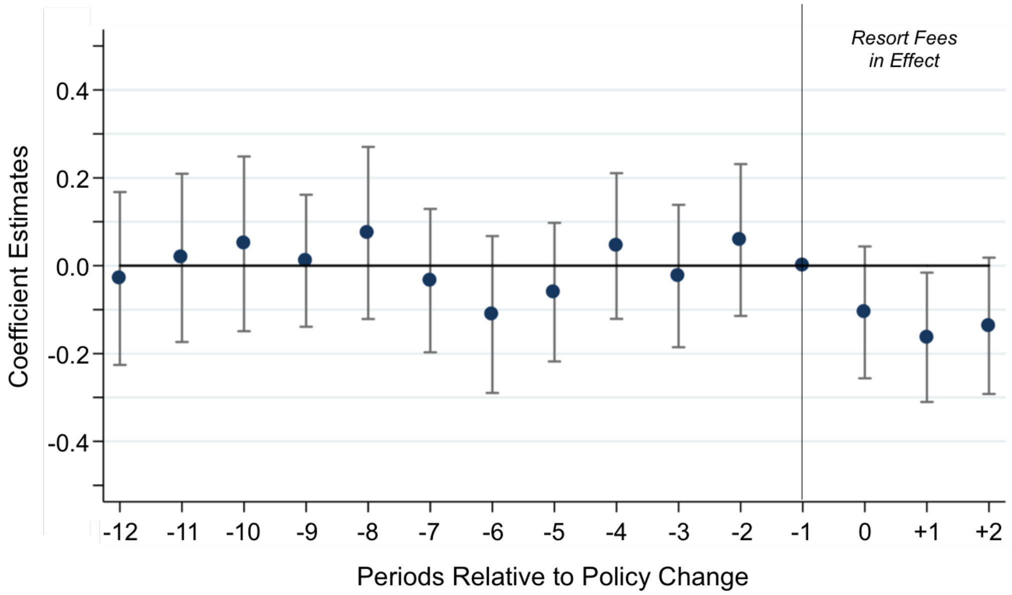
	Mean During Period: *Without Resort Fee*	Mean During Period: *With Resort Fee*	**Change**	**T-Test Significant at 5% Level?**
major_chain	32.9%	31.7%	-	No
optional_fees	43.5%	42.4%	-	No
Amenities:				
water_onsite	10.4%	12.5%	+	No
winter_onsite	6.8%	7.7%	+	No
tennis_onsite	11.4%	11.0%	-	No
golf_onsite	7.3%	7.7%	+	No
casino	2.6%	3.2%	+	No
restaurants	0.69	0.71	+	No
concierge	33.4%	40.0%	+	**Yes**
turndown	9.2%	9.4%	+	No
indoor_pools	0.23	0.23	+	No
outdoor_pools	0.71	0.71	+	No
beach_pool_amenities	14.5%	21.1%	+	**Yes**
fitness_classes	4.3%	6.8%	+	No
Health Club Onsite	7.2%	9.8%	+	No
Full-Service Spa Onsite	11.6%	14.3%	+	No

See Tables A2 and A3 for details on these variables. The last two items represent specific values for the categorical variables *fitness* and *spa*.

treatment group) is interacted with a set of time-to-treatment dummy variables. As depicted in Figure 2.7, coefficient estimates on this set of interaction terms are not statistically different from zero prior to the policy change but become negative following resort fee adoption.

In addition, Table A10 details a breakdown of traveler origin and trip type for both Expedia and TripAdvisor reviews, which are similar after accounting for the fact that Expedia has a larger proportion of "unspecified" trip types. (I also include these traveler-level controls in Model (5).) An important unobservable dimension on which TripAdvisor and Expedia reviews may differ, however, is the frequency of "fake" reviews – deceptive reviews posted by businesses in an effort either to inflate their own average ratings or damage those of their competitors. As Mayzlin, Dover, and Chevalier (2014) point out, the cost of writing a fake review is substantially lower on TripAdvisor than on Expedia, as the latter requires actually paying to book a room through an Expedia interface. This is not necessarily problematic to the D-in-D framework (and, indeed, may actually bias estimates for the treatment effect towards zero), so long as the propensity for fake reviews on either site does not change in a manner

Figure 2.7: Pre-Treatment Trends Around Resort Fee Adoption



Review data in this specification corresponds to that in the left-hand side of Figure 2.6, which includes hotels that adopted resort fees ***not*** *shrouded on Expedia. The dependent variable is individual traveler rating; circles indicate coefficient estimates on interactions between time-to-treatment dummy variables and an indicator variable for the "treatment group" (TripAdvisor). Bars represent 95% confidence intervals. The last month before resort fee adoption is the omitted interaction.*

that is correlated with changes in resort fee policies. To test for this empirically, I randomly select 150 reviews from each of four categories (Expedia pre- and post-policy change and TripAdvisor pre- and post-policy change) and manually run them through *reviewskeptic.com*, a website designed by Cornell University computer science researchers to test for fake hotel reviews (with claims of 90% accuracy). Table 2.9 details results. As expected, TripAdvisor seems to have more deceptive reviews than Expedia, but importantly, the frequency of fake reviews does not appear to change with the adoption of a resort fee.

Indeed, perhaps the most compelling argument in defense of the assumptions inherent to the D-in-D specification is the right half of Figure 2.6 (in which both Expedia and TripAdvisor reviewers are "treated" with the hidden fee), which depicts the two reviewer groups reacting similarly when exposed to the same shock. While it is not possible to formally identify a treatment effect in this case since both groups the hidden fee "treatment," it is still useful to quantify the correlation between ratings and "separate" fees as a point of reference. Running

Table 2.9: Reviews Flagged as "Fake" by Resort Fee Regime

	Without Resort Fee	**With Resort Fee**	**Difference**	**T-Test Significant at 5% Level?**
TripAdvisor	12.7% *19 out of 150*	13.3% *20 out of 150*	0.7%	No
Expedia	8.0% *12 out of 150*	6.7% *10 out of 150*	-1.3%	No

A random sample of 150 reviews in each of these four categories was selected for manual testing.
"Fake" reviews are those flagged as deceptive (vs. truthful) by *reviewskeptic.com*,
accessed September 2016 (see citation for Ott et al).

Model (5) as specified above on the set of reviews for hotels that made policy changes involving a "separate" resort fee, the coefficient on the interaction term (*tripadv * resort_fee*) is insignificant (in other words, ratings continue to move in parallel - exactly what we would expect). The coefficient estimate on the main effect, *resort_fee*, is -0.09 (with a t-statistic of -4.8 after adjusting standard errors for 248 hotel-clusters). This is also very much in line with what we would expect to observe absent the D-in-D framework, where we estimate in Model (5) a main effect of 0.05 and a treatment effect of -0.13 – summing to a total observed effect of -0.08. Indeed, all of these results also tie closely to the results obtained in the cross-sectional analysis of Section 2.4, where we estimated a coefficient for resort fees of -0.07 within the aggregate U.S. market. This consistency between all three sets of results lends confidence to the results in Table 2.7.

2.5.3 Treatment Effect Heterogeneity and Potential Mechanisms

If one of the chief objectives of this paper is to better understand why some firms adopt shrouded pricing and some don't, it is essential to explore how this estimated treatment effect may vary based on firm characteristics. To do this, I apply the D-in-D specification in Model (5) above to several key sub-samples of the data. Table 2.10 presents results for this analysis.

The top section of Table 2.10 generally supports H2: punishment is roughly three times more severe for lower-tier hotels (-0.3 points) versus mid- and high-tier hotels (roughly -0.1 points). The second two sections of this table attempt to shed some light on the mechanism

Table 2.10: Difference-in-Differences Results for Various Hotel Sub-Categories

Hotel Sub-Sample:	Coefficient Estimates For: Main Effect (*resort_fee_inc*)	Treatment Effect (*tripadv * resort_fee_inc*)	Number of Reviews
Low-Tier	-0.06	$-0.30***$	5,675
($stars \leq 2$)	(0.07)	(0.10)	*(44 Hotels)*
Mid-Tier	$0.05*$	$-0.11**$	19,168
($2 < stars < 3.5$)	(0.03)	(0.04)	*(84 Hotels)*
High-Tier	0.05	-0.08	13,036
($stars \geq 3.5$)	(0.04)	(0.05)	*(41 Hotels)*
Low-Tier ($stars \leq 2$)[a]			
Low-Price[b]	0.02	$-0.35**$	3,732
	(0.06)	(0.14)	*(28 Hotels)*
High-Price[b]	-0.18	$-0.24**$	1,943
	(0.15)	(0.12)	*(16 Hotels)*
Mid/High-Tier ($stars > 2$)			
Low-Price[b]	0.03	$-0.11**$	18,831
	(0.03)	(0.05)	*(66 Hotels)*
High-Price[b]	$0.12***$	$-0.12**$	13,373
	(0.04)	(0.05)	*(59 Hotels)*
Resort Amenities Provided[c]	0.05	-0.07	12,723
	(0.04)	(0.06)	*(48 Hotels)*
Resort Amenities *Not* Provided[c]	0.04	$-0.12***$	19,481
	(0.03)	(0.04)	*(77 Hotels)*
Chain-Affiliated	0.04	$-0.11**$	16,932
	(0.03)	(0.05)	*(70 Hotels)*
Independent	0.02	$-0.13***$	20,947
	(0.04)	(0.04)	*(99 Hotels)*

Standard errors parentheses reflect clustering at the firm level
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] *Note that only 2 firms in this category provide resort amenities, hence the sample cannot be split along this dimension.*
[b] *Low-price (high-price) defined as hotels with price less than or equal to (greater than) the corresponding MSA-market average for hotels of the same star category.*
[c] *See Tables A2 and A3 for details.*

driving the treatment effect in each of these respective market segments. In the low-tier segment, lower-priced hotels[41] are punished a bit more severely, whereas price relative to competitors does not seem to matter in the mid- and high-tier segments. However, what *does* seem to matter in the higher end of the market is whether or not a hotel provides typical

[41] Relative to other hotels in their respective markets of the same star category.

"resort amenities" – health clubs, spas, golf courses, etc. In this market segment, hotels that do not provide these amenities account for the majority of the observed negative relationship between resort fees and ratings. Results here suggest that the underlying mechanism may be different in these two segments of the market; specifically, a value-based mechanism seems important at low-end hotels, whereas a fairness-based mechanism may be at work elsewhere.

Generally speaking, these results are also consistent with heterogeneity in resort fee adoption patterns in the broader market. In particular, hotels in low star categories are substantially less likely to adopt resort fees, as are hotels that do not offer "resort amenities" (refer back to Table 2.1). One notable trend in adoption patterns, however, cannot be explained by these results: lower adoption rates for chain-affiliated hotels. Here, it seems that punishment for chain-affiliated hotels is similar (or even a little less[42]) than for non-chain-affiliated counterparts. The fact that chain hotels are so much less likely to adopt fees may thus at first seem surprising, particularly given that Luca (2011) finds chain-affiliated firms to be *less* affected on a revenue basis by changes in ratings. How should we reconcile this inconsistency? To a large extent, the explanation may be that hotel chains are extremely dependent on customer loyalty. Of the chains listed in Table A4, nearly all have loyalty rewards programs in place, and loyalty program members account for roughly 50% of room-nights booked at many of the largest brands (e.g., Hilton, Marriott, and Starwood).[43] To this end, chain hotels may tend to adopt fees at lower rates not because they are more concerned about the negative impact on their ratings, but rather because they are concerned about the impact of such fees on *customer loyalty*.

Finally, in addition to considering the "why" of the negative relationship between fees and ratings (i.e., altered perceptions of fairness, value, etc.), it is also important to consider the "how." The implicit presumption in this paper thus far has been that hidden fees work directly, causing a fixed set of consumers to leave lower ratings than they otherwise would.

---

[42]This may be explained by the fact that chain hotels sometimes *waive* resort fees for guests who are members of their loyalty programs.

[43]Per these companies' respective 10-K filings.

An alternative (but not mutually exclusive) explanation is that the presence of a hidden fee changes the propensity of various individuals to leave reviews. For example, consider a consumer who has had a fantastic hotel experience up until check-out and would, in the absence of hidden fees, leave a rating score of 5. If faced with a hidden fee, does this consumer instead leave a score of 3 or 4? Or does she simply decide not to bother with writing a review at all?[44] Either scenario will result in lower average ratings for the hotel, and it is impossible to definitively tease out which explanation is more relevant given the data at hand. Text from the reviews themselves, however, may begin to lend some color here. In particular, Table 2.11 below illustrates the fact that a relatively small portion of reviews from the treatment group actually mention "fee" (or related words/phrases) explicitly. And while those reviewers who mention fees do, indeed, leave substantially lower ratings on average, this alone is not enough to explain the magnitude of the treatment effect. This suggests either that hidden fees affect individuals' perceived experiences in relatively subtle/subconscious ways (hence the lack of more direct mentions in review content) or that fees change the motivation and propensity for otherwise "favorable" (or "unfavorable") reviewers to leave feedback.

Table 2.11: Explicit Mentions of Fees by Treatment Group in Review Text

	% That Mention Fees
$rating = 1$	6.3%
$rating = 2$	7.4%
$rating = 3$	6.7%
$rating = 4$	3.9%
$rating = 5$	1.8%
Overall	**3.5%**
Average Rating:	
Fee Not Mentioned	4.09
Fee Mentioned	3.46

[44] The flip side of this scenario is a traveler who has had a bad experience but is not particularly inclined to write a review. If hidden fees *increase* the likelihood that this individual decides to leave feedback, a similar result materializes.

2.5.4 Discussion

While the empirical evidence does support H1 – hidden fees result in lower ratings – the magnitude of this effect seems rather modest at roughly 0.15 points (on a rating scale that ranges from 1 to 5). Average ratings are just shy of 4.0, so the estimated treatment effect represents a decrease of 3-4% off of this mean value. It is important to reiterate that this estimated treatment effect is likely biased somewhat towards zero for two key reasons. The first was discussed in Section 2.3: some members of the treatment group (i.e., TripAdvisor reviewers) don't actually receive the hidden fee "treatment." This is because *anyone* can write a review on TripAdvisor, so some Expedia buyers (i.e., members of the control group) undoubtedly account for some portion of the reviews in this setting. There is also a strong argument, however, that results are biased towards zero due to selection effects. The previous sub-section illustrated that hotels for which punishment is likely to be large (e.g., lower-tier hotels) are substantially less likely to adopt fees. Turning this on its head implies that the aggregate treatment effect estimated here is smaller in magnitude than would be expected if, for example, resort fees could be randomly assigned to hotels.

If bias is small, and -0.15 is a fairly accurate estimate for this treatment effect, then what are the implications for firm performance? Recall from Section 2.2 that various studies (in the context of Yelp as well as two different OTAs) have estimated the impact of a 1-point change in ratings (on a 5-point scale) to correspond approximately to a 10% increase in revenues. Scaling this figure linearly, we can ballpark an associated decrease in revenue of roughly 1.5% due to decreases in ratings driven by the adoption of hidden fees.

How does this compare with potential *increases* in revenue due to hidden fees? The data indicates that base room rate pricing effectively doesn't change when a fee is adopted ($132 vs. $135), and resort fees are, on average, roughly 10% of room rate. So if firms charge the same base prices and continue to attract the same number of customers, then the adoption of a hidden fee will directly boost revenue by 10%. It may be more realistic to assume that fees do dampen demand (i.e., booking volume) at least *slightly*,[45] so perhaps the increase in revenues associated with hidden fees is less than 10% after accounting for some dip in quantity. In any case, the financial benefits of obfuscation likely outweigh the reputational costs under these baseline assumptions – at least for many firms. Given the nature of the sample, however, this is not entirely surprising, as these results are derived only from data where firms have, at some point, chosen to adopt a resort fee (so ostensibly, the benefits *should* outweigh the costs for these firms). It is important to also keep in mind, though, that there may be other potential costs to obfuscation in addition to the reputational effects explored here, e.g., decreased customer loyalty (a major concern for chain-affiliated firms, in particular) or logistical/labor costs associated with handling disgruntled patrons at the check-out desk. Recall that only 7% of hotels charge resort fees. If the financial gains associated with obfuscation really outweighed the total cost so starkly, we would expect this number to be much higher.

Finally, it is important to address external validity: to what extent might these results apply in other industry settings and in the context of other types of practices designed to exploit boundedly rational consumers? Certainly these findings suggest that when online feedback mechanisms exist, consumers may be able to at least partially deter firms from engaging in practices that they deem to be undesirable by punishing them with lower ratings. For this to be the possible, though, consumers must, at the very least, *recognize* that they are being exploited. While this is likely the case in many contexts (particularly with regard to shrouded surcharges – ultimately consumers have to pay them, so in most cases they do not remain hidden forever), it may not hold in some of the most high-stakes settings. For example, in the case of hidden 401(k) fees, consumers may never actually realize that the fees exist if they are automatically deducted and individuals do not pay close attention to their account statements over time. This specific example also raises the point that there are many good and services where online feedback mechanisms are not commonly utilized

[45] Arguably some consumers do recognize the fee as an effective price increase and adjust their purchase decisions accordingly.

(e.g., financial services). Without this particular market feature, it less clear what sort of punishment firms might face for behaving badly. Loss of loyalty in repeated transaction settings may be an effective deterrent, but this is not directly examined here. Additional research is needed to shed light on this issue.

2.6 Conclusions

The notion that consumers may punish firms for price obfuscation (and deceptive behavior more generally) is hardly new, yet surprisingly little research exists to support it. This paper begins to build toward a theoretical framework for thinking about this issue, providing well-identified empirical evidence on one mechanism by which firms may be punished for deceptive pricing practices: reputational damage in the form of lower ratings. Using data from the U.S. hotel industry, I document a robust negative relationship between hidden resort fees and online traveler ratings. To support a causal interpretation of this result, I employ a difference-in-differences framework to exploit the fact that, for a subset of hotels, *resort fees are not actually hidden* from customers booking via Expedia and subsidiary brands. And since traveler reviews on Expedia sites are restricted to users that have verifiably booked through an Expedia interface, corresponding ratings should not reflect any "hidden fee effect." In contrast, resort fees *are* hidden from travelers who reserve these same hotels via other booking channels, and any corresponding negativity associated with these hidden fees will thus be reflected in reviews on sites such as TripAdvisor, where travelers from many different booking channels submit ratings.

Empirical results indicate that the adoption of a hidden fee decreases subsequent traveler ratings by roughly 0.15 points (on a rating scale that ranges from 1 to 5). This effect is substantially larger for lower-tier firms, which is consistent both with a potential fairness-based mechanism (i.e., consumers punish firms for shrouded surcharges more when they are perceived as less "fair") and with a potential value-based mechanism (i.e., shrouded surcharges, either consciously or subconsciously, have a negative effect on consumers' perceived value – an effect that is likely exacerbated in more price-sensitive segments of the market). Importantly, this variation also helps to explain heterogeneity in resort fee adoption patterns: lower-tier firms are much less likely to adopt fees.

Benchmarks from existing literature suggest that a reduction in ratings by the baseline amount of 0.15 points is associated with a decrease in revenue on the order of magnitude of 1-2% – not an inconsequential figure, but still probably not enough to outweigh the revenue gains from price obfuscation (which are likely more in the ballpark of 5-10%). There are several reasons to argue, however, that the treatment effect estimated here is best understood as a lower bound for the true effect of hidden fees on ratings. Most notably, all else equal, firms should be more likely to adopt hidden fees when the expected reputational damage is *lower*. In contrast, when expected reputational damage is high, hotels will be less likely to adopt fees (and thus less likely to be included in the difference-in-differences sample here – biasing the estimated treatment effect towards zero). By definition, the D-in-D sample can only consist of firms that have, at some point, adopted a resort fee. It is thus not surprising that the estimated benefits of obfuscation seem to outweigh the estimated costs. Ostensibly, these firms would never have adopted a fee in the first place if this were not the case.

Regardless of their precise magnitude, the empirical results presented here clearly establish that hidden fees do, indeed, negatively impact ratings. This speaks to a critical missing piece in the price obfuscation literature, which has heretofore focused on the financial gains that motivate firms to obfuscate. Here, we see that there are also costs – which helps to explain why obfuscation is not *more* widespread (in the absence of any associated costs, we would expect to see firms adopting deceptive tactics much more gratuitously). It must be emphasized, however, that this paper on its own cannot fully reconcile the disparity that exists between between theory and practice. As noted above, the reputational costs associated with obfuscation are probably not large enough to outweigh the associated revenue gains in a large number of cases. But reputational cost is only one way in which firms may be punished for deceptive pricing; an additional (potentially more important) way in which consumers may retaliate is by simply taking their business elsewhere. More research is needed to understand the potential effect of obfuscation on customer loyalty in repeated transaction settings.

This paper's findings are also highly relevant to the literature on corporate social responsibility, which explores the various ways in which firms may be financially rewarded for "doing good." Here, conversely, we have novel empirical evidence to suggest that firms may be punished for behaving badly. This result motivates further research on the potential costs of deceptive tactics more generally – an area where there has been very little work to date, either in the way of theory or empirical evidence. It also raises the question of whether or not there may be rewards for firms who act honestly and transparently in their dealings with consumers and other stakeholders. The CSR literature has been largely focused on the way in which activities such as philanthropy and environmental efforts may benefit firms by boosting their reputations as fair and honest actors. In light of findings presented here, perhaps more attention should be paid to the question of whether (and how) companies may reap similar benefits *simply by behaving honestly.*

Certainly the empirical results presented in this paper are of direct practical importance to managers in many industries, particularly in online settings, where reputation (in the form of ratings) has been shown to be a critical driver of firm performance. This paper also highlights the need to think about the costs of price obfuscation more generally. Potential losses in customer loyalty, for example, may be a chief concern in many industry settings. And while price obfuscation is an issue that managers in *many* industries contemplate, managers in *all* industries must grapple with issues of transparency, corporate honesty, and the use of potentially deceptive tactics. Thus, the extent to which firms may be punished for deceptive tactics or rewarded for transparency and honesty must be a critical question for researchers in strategic management. This paper has begun to address this issue by demonstrating that there are tangible consequences to price obfuscation in the form of lower ratings. This evidence, however, speaks to only one aspect of a much broader set of research questions. There is a great deal of work left to be done.

CHAPTER 3

Price Obfuscation: From Theory to Practice

3.1 Introduction

The existing literature on price obfuscation is quite fragmented. Various academic disciplines have developed their own vocabularies to describe these practices, and, indeed, even *within* disciplines, there is often an abundance of confusing and sometimes inconsistent terminology from author to author. Different disciplines also, quite naturally, diverge in terms of the angle from which they approach the issue. For example, scholars in marketing and psychology have tended to focus on the extent to which consumers are susceptible to various obfuscation tactics and the behavioral explanations underlying these findings. Economists have, to a large extent, been focused on explaining why firms obfuscate in the first place, when conventional theory (e.g., Milgrom, 1981; Grossman, 1981) suggests that these practices should not be profitable. My own approach to the topic begins with an important observation: empirically, we observe a great deal of heterogeneity, both within and across industries, with respect to the prevalence of price obfuscation. This heterogeneity is not well explained by existing theory, although many of the studies discussed herein yield important insights. Ultimately, the central objective of this chapter is to organize these insights and marry them with illustrative evidence from case studies to begin to build a more unified framework for understanding why, in practice, some firms obfuscate while others do not.

Before beginning, it is helpful to reiterate what, precisely, "price obfuscation" means in this context. As initially outlined in the very first section of this dissertation, I offer the following working definition: any tactic utilized by firms for the purpose of preventing consumers from becoming fully informed about market prices. In other words, obfuscation involves actions intended to suppress price information. Discerning a firm's intent can make obfuscation difficult to identify conclusively in practice (I discuss this more in Section 3.2.3), but it is precisely the *intent* to suppress information that is obfuscation's defining characteristic. Buyers might fail to gain complete information or fail to choose the best price for a number of reasons (e.g., if search costs are exogenously high, if there is exogenous noise in the prices that buyers are able to observe, etc.). Situations such as these, however, are not examples of obfuscation by the definition that I employ here (they involve no intent on the part of firms), and they are not the focus of this discussion.[1]

The remainder of this paper proceeds as follows: Section 3.2 describes various forms of price obfuscation in more detail and classifies these practices along some fundamental dimensions. Here, I also introduce and categorize prevailing theories, summarize corresponding predictions (equilibrium outcomes, welfare implications, etc.), and propose some questions that might serve as a starting point for determining the extent to which a given model might apply in various empirical settings. In Section 3.3, I turn to the central question of heterogeneity. The empirical literature clearly suggests that there are substantial revenue gains associated with obfuscation – yet not all firms obfuscate. I thus frame this discussion around the various factors that might weigh *against* potential revenue gains (i.e., potential costs) as well as the factors that might *moderate* potential gains. Finally, in Section 3.4, I provide four case studies that underscore and further develop some of the insights from Section 3.3. In particular, these cases illuminate the way in which a firm's unique strategy and market position influence its incentives to obfuscate, or, conversely, to buck competitive pressure and instead pursue "strategic transparency." Section 3.5 concludes and offers directions for future research.

[1] For an excellent survey that *does* cover these topics, see Grubb (2015).

3.2 Defining and Categorizing Obfuscation

3.2.1 Classifying Various Forms of Price Obfuscation

Obfuscation can be classified along multiple dimensions. In particular, I find it useful to draw distinctions based on both the mechanism of obfuscation and the type of informational failure that results. Table 3.1 provides an illustration. There are two fundamental types of mechanisms here: price obfuscation can either occur via the exploitation of behavioral weaknesses (top row of Table 3.1) or via the pursuit of activities that make price search more lengthy and/or laborious (bottom row of Table 3.1). There are also two fundamental types of informational failures that might occur as a result. Depending on the tactics utilized, consumers may either mistakenly believe that prices are lower than they actually are, or, alternatively, they may be generally confused or uncertain about prices and thus unable to effectively compare them across competitors.

Table 3.1: Modes of Price Obfuscation

		Informational Failure:	
		Prices Mistaken for Lower Than They Actually Are	General Confusion/Uncertainty About Prices
Obfuscation Occurs Via:	Exploitation of Bounded Rationality	**Trickery**	**Confusion**
	Creation of Search Costs	NA	**Obstruction**

Combining these dimensions results in three possible "modes" of obfuscation, which I distinguish as follows:[2]

[2]There are three rather than four combinations here as I know of no tactics whereby increasing the cost of search results in consumers mistakenly perceiving prices as lower than they actually are. This type of mistake seems to be a fundamentally behavioral one.

- ***Trickery:*** Exploiting behavioral limitations/mistakes in a manner that deceives consumers into perceiving that prices are lower than they are in reality. For example, if an inattentive consumer fails to notice a shrouded surcharge (or notices it but inappropriately accounts for it in her calculation of total price), her perceptions will be anchored on the (misleadingly low) base price.[3]

- ***Confusion:*** Exploiting behavioral limitations/mistakes in a manner that results in consumer confusion or uncertainty about prices. For example, cognitively limited consumers may be unable to assess/compare prices when they are presented in complex multi-dimensional formats or in frames that differ across competitors. In these cases, theoretical models tend to assume some element(s) of randomness in consumers' ultimate decisions. (I discuss this more in subsequent sections.)

- ***Obstruction:*** The pursuit of activities that make price search more lengthy and/or laborious. As with confusion, this may involve various forms of price complexity (here, though, it is effort and/or time that consumers lack, not cognition); obstruction may also involve stalling tactics – for example, requiring a consumer to spend time clicking through several dozen screens before providing them with price information. These tactics effectively limit the extent to which consumers gain full information about market prices in equilibrium.

There are important differences between these modes of obfuscation. While both "trickery" and "confusion" depend on the presence of myopic consumers in the market, they differ in that (assuming obfuscation is costless) "trickery" seems to be individually rational for firms rather trivially in most cases. For example, if a firm can partition out some portion of its price into a mandatory shrouded surcharge that it knows (at least some) consumers will either not notice or not account for properly, then this is a strictly dominant strategy. In other words, if a firm can make prices look misleadingly cheap and competitors have no way to effectively expose this deception, then of course the only equilibrium is for all firms to obfuscate in this manner.[4] In contrast, if firms can only *confuse* consumers about prices – without any influence over the particular direction of the uncertainty – then the individual rationality of obfuscation is much less straightforward.[5]

---

[3]See Tversky and Kahneman (1975) for details on anchoring and adjustment theory; see Ahmetoglu et al. (2014) and Greenleaf et al. (2015) for more on the psychological processes underlying consumers' reactions to partitioned pricing specifically.

[4]When surcharges are avoidable rather than mandatory, this conclusion may not always hold. Gabaix and Laibson (2006) address this case.

[5]Several theory papers, however, do establish that obfuscation via "confusion" will be individually rational

In some sense, the distinction between "confusion" and "obstruction" is less important. For example, suppose consumers are selecting a bank. This choice typically involves evaluating a complex set of fees: ATM fees, overdraft fees, minimum balance fees, etc. A myopic consumer might lack the cognitive ability to evaluate options along all of these dimensions,[6] rendering her unable to effectively compare prices. Alternatively, a rational consumer might be quite *able* to accurately comprehend prices in this setting, but simply decide that sifting through this complicated set of prices across all products is simply *not worth the effort*. In the first case, consumers lack cognitive ability, while in the second case, they lack time and/or willingness to search. In both cases, however, the essential outcome is that consumers ultimately make choices without complete information.

One key difference between these scenarios, though, is – to borrow from a former Secretary of Defense – the extent to which uncertainty about prices is (from the perspective of consumers) a *known* unknown versus an *unknown* unknown. This might matter for several reasons. For one, consumers may react quite differently *ex post* in these two scenarios. Suppose our consumer from the prior paragraph has selected a bank and subsequently incurs an overdraft charge. Behavioral research[7] suggests that a myopic consumer may be more inclined to blame the bank (for confusing her), while a time-constrained consumer may be more likely blame *herself* for not paying more attention to the fee structure. This difference has implications for firms in cases where reputation is an important asset and/or transactions are repeated over time. In addition, there are, arguably, ethical differences between these scenarios that might matter to managers and/or lawmakers. And finally the welfare implications are potentially different in each case, depending on the specifics of additional assumptions. I discuss each of these issues more throughout subsequent sections of this paper.

In practice, it is often difficult to determine which mechanism (bounded rationality or

under certain assumptions/conditions. I discuss this more in subsequent sections.

[6]There is substantial evidence (see Grubb, 2015 for a review) that boundedly rational consumers struggle to evaluate prices when they are presented as complex vectors.

[7]For example, Lee and Han (2002).

search costs) is at work in any given situation. What we do observe with some clarity are the specific actions that a firm takes. I detail four commonly utilized (and commonly studied) tactics below. Quite often two or more of these tactics are used in combination (e.g., surcharges are, by definition, partitioned; they are also commonly shrouded).

- ***Partitioning:*** Separating the price of a good into a base price plus one or more additional mandatory parts. "Partitioned pricing" (a term coined in the marketing literature) differs from "drip pricing" (the term more commonly found in the economics literature) in that drip pricing also involves a temporal component (see "stalling" below) – here, additional fees continue to "drip" as the consumer moves through the purchase process. With partitioned pricing, in contrast, all components are presented up front.

- ***Shrouding:*** Reducing the visibility of price (or some components of price). Most often this involves relegating a surcharge to fine print or, perhaps, not listing it at all.

- ***Complexity:*** Increasing the level of cognitive difficulty (or costly effort) required to effectively process prices and/or price comparisons. This includes a broad set of activities: multi-dimensional price formats,[8] confusing or overly technical language, large menus of options (that might include dominated choices), inconsistent price framing (versus other products), etc.

- ***Stalling:*** Increasing the time required for a consumer to learn the (total) price of a good, i.e., intentionally raising search costs.[9] Stalling tactics are similar to shrouding tactics in some ways, but they are carried out along the dimension of time rather than visibility.

3.2.2 Models of Price Obfuscation

Table 3.2 classifies key models both by mode of obfuscation (based on each model's implicit assumptions) and by the specific information-suppressing action(s) that firms are allowed to take. The earliest contribution here – Ellison (2005) – is, in many ways, one of the most influential papers in the obfuscation literature. But it is not, strictly speaking, a paper

[8]This is distinct from partitioned pricing in that partitioned pricing involves a base price (on which consumers are presumed to anchor) and surcharges (that are less salient). In multi-dimensional formats, all components of price may be equally (un)salient.

[9]Car salesmen, for example, are notorious for intentionally drawing out the sales process once potential buyers enter negotiations.

Table 3.2: Price Obfuscation: Key Theoretical Models

Paper	Jargon	Mode of Obfuscation	Key Firm-Level Choice Variable(s)	Key Assumptions	Equilibrium Outcome	Welfare Implications
Ellison (2005)	*"Add-On Pricing"*	N/A *(not technically obfuscation)*	• N/A *(firms simply choose prices)*	• Strength of horizontal preferences and vertical tastes positively correlated • Search is (exogenously) costly	Add-on pricing is jointly rational due to adverse selection	Equilibrium profits for firms increase; total deadweight loss is greater than in standard price discriminating equilibrium
Gabaix & Laibson (2006)	*"Shrouded Add-Ons / Surcharges"*	Trickery	• Firms choose whether or not to **shroud** prices for an avoidable add-on good	• A fraction (α) of "myopic" consumers do not observe add-on price if shrouded • Consumers may exert costly effort to substitute away from add-on	Shrouding is individually rational if α is sufficiently large	Firms earn zero profit regardless of α; in a shrouded price equilibrium, welfare falls as "sophisticated" consumers exert costly effort to avoid the add-on
Spiegler (2006)	*Multi-Dimensional Pricing*	Confusion	• Firms choose the level of price **complexity**	• Cognitively limited buyers compare prices using a heuristic ($S(1)$)	Obfuscation is individually rational; optimal complexity is an increasing function of the number of competitors	Depending on specific assumptions, social surplus is either flat or decreasing in the number of competitors (and any losses are borne entirely by consumers)
Carlin (2009)	*Strategic Price Complexity*	Obstruction	• Firms choose the level of price **complexity**	• Based on firms' selected level of price complexity, some consumers with high search costs remain "uninformed" and choose products at random	Obfuscation is individually rational; optimal complexity is an increasing function of the number of competitors in the market	Firms capture positive profits in equilibrium; social surplus not addressed (although persistent price dispersion in equilibrium suggests inefficiency)
Ellison & Wolitzky (2012)	*Obfuscation*	Obstruction	• Firms can take actions (costless or costly) that increase the amount of time that consumers must spend to learn a firm's price	• Consumer disutility for time spent shopping is strictly convex	Obfuscation is individually rational unless the exogenous component of search costs is sufficiently large	Firms capture positive profits in equilibrium; surplus declines (both due to higher prices and due to the additional search costs imposed on consumers)
Chioveanu & Zhou (2013)	*"Frame Complexity vs. Frame Differentiation"*	Confusion	• Firms choose both price complexity and price frame	• Consumers can be confused both by complexity and by inconsistency in frames across firms • Confused consumers select products at random	Firms randomize both price complexity and price frames; firms use complexity more as the number of competitors increases	Firms capture positive profits in equilibrium; consumer surplus may decrease with more competition (assumption dependent)

Additional models include Wilson (2010), who explores asymmetric equilibria when obfuscation raises search costs; Piccione and Spiegler (2012), whose model is similar to Chioveanu and Zhou's; Gu and Wenzel (2013), whose main result is that more prominent firms are more likely to obfuscate; and Dahremoller (2013) and Wenzel (2014), both of which build on Gabaix and Laibson (2006) with some small modifications in assumptions.

about obfuscation at all! Importantly, firms do not take any actions here that suppress information. Search costs are exogenous, and consumers are assumed to be rational (correctly inferring all prices in equilibrium). While these conditions result in positive equilibrium profits for firms, this result is not due to obfuscation – rather, this model shrewdly characterizes (a particularly interesting variety of) price discrimination.

Gabaix and Laibson (2006) initially grew out of Ellison (2005), but the authors ultimately take a markedly different approach. Here, (some) consumers are boundedly rational, and firms can exploit these "myopic" consumers by shrouding prices for add-ons. Notably, the authors focus primarily on the case in which these add-on purchases are avoidable. They relegate the treatment of shrouded *mandatory* surcharges to a short footnote – presumably because it is not a particularly interesting case from a modeling standpoint. That they do not place more emphasis on this scenario is rather unfortunate, however, both because mandatory shrouded surcharges are quite common in practice, and because their ultimate conclusion is quite strong: if there are *any* myopic consumers in the market, then firms will always choose to shroud mandatory surcharges.

Spiegler (2006) and Carlin (2009) both offer models in which firms choose price complexity. The former assumes that this complexity confuses boundedly rational consumers (who subsequently make decisions using heuristics), while the latter takes the view that obfuscation may raise search costs enough that some consumers simply remain uninformed about prices. (These two models, along with some of the others mentioned in Table 3.2, offer important predictions regarding the way in which competition affects firms' incentives to obfuscate; I defer a discussion of these findings until Section 3.3.3.) Similarly to Carlin (2009), Ellison and Wolitzky (2012) model obfuscation as an action that increases consumers' search costs. Their assumptions, however, are not as strong as Carlin's, lending additional weight to their key result: that obfuscation is often individually rational.[10] Finally, Chioveanu and Zhou (2013) present a different sort of model, in which there are two key ways that firms can obfuscate –

[10] In Carlin (2009), one firm's obfuscation is assumed to affect the search incentives of the entire customer pool, while in Ellison and Wolitzky (2012), one firm's obfuscation only affects the consumers who visit that firm.

by choosing the complexity of their price formats *and* by choosing the type of format, i.e., the "frame." Here, confusion among consumers arises from both complexity and from differences in price frames among competitors (e.g., "buy one, get one free" vs. "three for $5").

On net, what do these models tell us about obfuscation's effect on welfare? The prevailing viewpoint in the popular press is that price obfuscation is bad for consumers and good for firms. And, indeed, a common theme among these models is that consumers tend to be harmed. It is worth pointing out, though, that obfuscation does *not* always make firms better off. In particular, when obfuscation occurs via "trickery" – i.e., fooling boundedly rational consumers into thinking prices are lower than they really are – firms might still earn zero profits in equilibrium. The intuition here is that all profits earned on shrouded surcharges will be competed away via lower prices on the base good (which even boundedly rational consumers observe accurately).

In contrast, if firms can create general confusion or obstruct consumers' ability to obtain price information, then they will capture positive profits in equilibrium. Social surplus, however, still decreases, though the amount by which it decreases depends on the circumstances. In particular, if obfuscation occurs via "obstruction," then there may be multiple sources contributing to a decline: 1) prices are higher than is efficient; 2) obfuscation creates search costs for consumers (that would otherwise not have existed); and 3) obfuscation may itself be costly (i.e., firms must spend time and/or resources to engage in it). This last insight – that obfuscation costs firms time and resources that would be more productively utilized elsewhere – echoes Nalebuff and Ayres (2003), who argue that "companies should spend less time trying to fool customers with hidden charges and devote more effort to *competing on differences that really matter*." In other words, competing via obfuscation is socially unproductive and, in a sense, lazy. One might wonder the extent to which obfuscation serves as a substitute for other activities (developing cost saving measures, investing in innovation) that actually create value. This seems an important avenue for further research.

3.2.3 Determining Which Model Applies

The assumptions and machinations of existing price obfuscation models fit real-world applications to varying degrees. Given an empirical setting, a useful first question to ask is always: what is the type of informational failure at hand? Are firms deceiving consumers into believing that prices are artificially low? Or are consumers generally confused (or otherwise unable to obtain complete information)? As discussed in the previous section, there are important differences between these underlying mechanisms in terms of predicted equilibrium outcomes.

A second key question is: what are firms actually choosing, versus what is exogenous to the market setting? In Gabaix and Laibson (2006), for example, firms' critical choice variable is whether or not to *shroud* prices for add-ons. That the add-ons are *partitioned* is simply assumed. There are many empirical scenarios (e.g., printers and ink cartridges, as the authors propose) where this theoretical framing seems to fit fairly well. There are others where it is questionable. For example, the authors specifically mention avoidable add-on goods in the hotel industry (wireless internet, parking, phone calls, room service, etc.). Is the shrouded nature of these fees really a choice that firms make intentionally? Or is it rather that their shroudedness is an exogenous feature of the market? It seems reasonable to surmise that such information would be quite difficult to effectively convey to travelers *ex ante*. In contrast, what firms *do* clearly control in this scenario is whether or not the add-on good is partitioned out from the base price. Most hotels offer wireless internet, parking, etc. free of charge, so the very fact that some firms opt instead to price these services separately implies a distinct choice. But if search costs are exogenously high and firms' key choice is whether or not to partition, then Gabaix and Laibson's model is probably not a good fit for the empirical setting. Rather, Ellison's (2005) price discrimination model seems more appropriate.

Indeed, to this very point, distinguishing price obfuscation from strategies such as price discrimination and unbundling is often a challenge, especially in cases where these tactics might look quite similar in practice. Some tactics (e.g., shrouded mandatory surcharges) are relatively unambiguous – there are very few reasons for shrouding a mandatory component of price other than an intent to mislead. In other cases, things are not so clear-cut. For example, are banks' fee structures complicated for the purposes of obfuscation, or are they complicated by necessity because the *product* is complicated? Are avoidable add-ons in the airline industry price obfuscation, or just unbundling? (I discuss this specific example in my last case study.) Here again, it is useful to ask what the firm is really *choosing*, versus what features are inherent to the market. Gabaix and Laibson (2006) offer that consumer surveys can help to detect, in practice, whether or not buyers are aware of shrouded add-ons. Another strategy for determining likely obfuscation is to examine firm-level or industry-level lobbying efforts. If players are pushing back strongly against policy measures designed to increase price transparency or required disclosures, then it seems only logical to suspect that current pricing policies are, at least to some extent, designed to suppress this information.

3.3 Understanding Heterogeneity in Obfuscation

In this section, I organize findings from a range of literatures into a common framework for thinking about what factors drive (or, alternatively, mitigate) obfuscation. I structure the majority of this discussion through the lens of the following basic tenet: that for a firm to obfuscate, the associated incremental revenue must outweigh incremental costs. Accordingly, I discuss the factors – both at the firm-level and the market-level – that might increase or decrease the respective sides of this equation. Of course in reality, endogeneity complicates the matter. Firms' decisions regarding price transparency may influence aggregate market conditions; moreover, one firm's decision to obfuscate (or not) may affect other firms' decisions in this regard. I try to address these sorts of issues during my discussion in Subsection 3.3.3.

3.3.1 How Large Are the Potential Gains from Obfuscation?

A number of papers examine the extent to which consumers are susceptible to various forms of price obfuscation. Many of these papers are focused on understanding the underlying

Table 3.3: Key Empirical Results on the Potential Gains from Price Obfuscation

Paper	Type of Study	Jargon	Mode of Obfuscation	Setting/Description	Key Results
Morwitz, Greenleaf, & Johnson (1998)	Experiment	*"Partitioned Pricing"*	Trickery	• Subjects (N=199) asked to place sealed bids for a jar of pennies • All participants asked to report their perceived value of the jar along with their bid • Teatment group informed that the winner must pay a buyer's premium of 15% in addition to bid (i.e., price is partitioned into two parts)	• Ratio of total bid (inclusive of buyer's premium) to perceived value was significantly higher in the treatment group (average bid/value=.885) than in the control group (average bid/value=.787) • Implication: the treatment group bid 12.5% more on average (largely ignoring the partitioned component of price when formulating bids)
Ellison & Ellison (2009)	Observational	*"Obfuscation"*	Obstruction	• Sales and cost data from firms on an internet price search engine (Pricewatch), utilized primarily by "savvy" computer parts shoppers	• Obfuscation increases markups from a predicted 3-6% to about 12%
Chetty, Looney, & Kroft (2009)	Field Experiment	*NA (Taxes)*	Not Obfuscation (but related to trickery)	• Tax-inclusive prices posted for products in three supermarket categories (cosmetics, hair care, and deodorant); other categories exclude tax in posted prices • Difference-in-difference setup using scanner data to examine quantities sold before and after tax-inclusive prices (treatment) implemented	• Posting tax-inclusive prices (tax rate = 7.4%) reduces demand by 8% • Implication: taxes (a partitioned component of price) are largely not accounted for in purchase decisions
Brown, Hossain, & Morgan (2010)	Field Experiment	*"Shrouded Charges"*	Trickery	• iPods sold on two online auction platforms • Amount and disclosure level of shipping charges are varied	• When shipping charges were clearly disclosed, revenue effect ambiguous • When shipping charges were shrouded, revenues increased by 5-7% on average
Kalayci & Potters (2010)	Experiment	*"Price/Product Complexity"*	Confusion	• Two sellers each choose price complexity (a number of dimensions between 1 and 5) and set prices • Buyers are shown prices and have 15 seconds to decide which seller's good to buy	• Buyers make more mistakes as price complexity increases; specifically, if either seller presents a multi-dimensional price, the probability of making a mistake increases by 35% • Transaction prices increase with price complexity
Muir, Seim & Vitorino (2013)	Observational	*"Drip Pricing, Shrouded Add-Ons"*	Trickery	• Detailed data from Portuguese driving schools (students purchase a base course in instruction and may face additional shrouded charges if they must retake exams)	• Empirical results fit predictions of a Gabaix and Laibson (2006) style model • A substantial portion of schools' variable profits derive from add-on fees; markups for the base good, but not the add-on, decline in the number of competitors

behavioral mechanisms and/or the impact on consumers.[11] In contrast, my focus here is on understanding the implications of existing work from the perspective of the *firm* – i.e., if a firm opts to obfuscate, how large are the potential financial gains? Table 3.3 summarizes some key empirical results.

On net, the evidence overwhelmingly suggests that the financial gains from obfuscation are quite substantial. In particular, all of the experimental papers on surcharges reach essentially the same conclusion: when they are shrouded (and even sometimes when they are not), consumers do not properly take surcharges into account. The addition of a shrouded surcharge increases revenue substantially in all of these papers – sometimes dollar for dollar. There is also some evidence here that obstruction and confusion are effective tactics. Ellison and Ellison (2009) find that markups are higher than expected when firms' frustrate the search process, and Kalayci and Potters (2010) find that buyers make more mistakes and transaction prices increase with complexity in an experimental setting.

Very little work has been done to examine the extent to which these sorts of financial gains may dissipate over the longer-term, and experimental studies, in particular, are poorly suited to shed light on this question. There are several factors that might impact the persistence of these gains – e.g., the extent to which consumers learn to avoid firms' tricks with repeated interaction. Some of the results that utilize observational data, however, suggest that even firms who have been engaging in these practices for some length of time are still able to gain from them. The elevated markups in Ellison and Ellison (2009), in particular, are striking given that the market they study is one where buyers are savvy and experienced.

3.3.2 Are There Costs to Obfuscation?

The empirical evidence, then, is clear: the financial gains associated with obfuscation are likely quite substantial. In practice, though, we do not see all firms engaging in these practices – which suggests that there may also be associated costs. Below, I summarize

[11] For a survey of this literature, see Ahmetoglu et al. (2014) and Greenleaf et al. (2015).

some of the potential ways in which obfuscation might be costly, citing insights from existing literature where applicable. One theme that emerges right away is that we understand much less about the role that these potential costs might play – there has been very little research in this area.

Implementation Costs

In most cases, price obfuscation simply involves making choices about the format in which price is presented (e.g., should price be listed as an all-in figure or as a combination of four partitioned components? Should fees be listed prominently or in tiny print?) In these cases, implementation costs do not seem particularly relevant as a mitigating force. There is zero cost associated with changing the font in which fees are listed on a website. There may be some cases, however, where implementing obfuscation is in fact costly in a meaningful way – particularly in cases that involve stalling tactics. For example, a car dealer that instructs sales associates to stall potential buyers will, at least in theory, incur higher labor costs.

Reputation

The wealth of websites and consumer groups devoted to banning various forms of price obfuscation suggests that consumers find these tactics objectionable. (The extent to which a distaste for obfuscation may actually outweigh other factors is not at all clear, but it seems uncontroversial to submit that in general, consumers have a disutility for obfuscation and would rather purchase from an "honest" firm, all else equal.) Given this, there are at least two ways in which obfuscation may cause firms harm from a reputational standpoint. The first occurs in settings where transactions may be repeated, and obfuscation results in a loss of future business from disgruntled buyers. Alternatively, in market settings where publicly observable feedback mechanisms (e.g., Yelp and similar sites) are available, consumers may assign low ratings to firms that obfuscate. In this case, firms can be "punished" for obfuscation even when transactions are not repeated and the set of buyers in the market is different each period. Chiles (2017) finds evidence of this in the U.S. hotel industry: firms that adopt shrouded surcharges subsequently receive lower traveler ratings.

Logistical Complications

Just as obfuscation may be damaging to reputation over the long-term, it may also make existing customers more difficult to deal with in the short-term. For example, hotels that charge resort fees are frequently in the situation of having to handle angry customers at check-out. This sort of backlash might be costly if firms end up needing to enlist/train a larger number of customer service staff than they otherwise would. Obfuscation may also shape consumer behavior in unforeseen and inconvenient ways. In the airline industry, for example, baggage surcharges have been quite effective at reducing the number of customers who check bags – but from a logistical standpoint, it is not at all clear that this is actually optimal. The increased number of travelers opting for carry-ons has resulted in longer security lines and substantially more chaos during the boarding process, both of which may actually cost airlines by contributing to more frequent flight delays.

Ethical Considerations

Even after detailing several tangible ways in which obfuscation may be costly for firms, the empirical evidence in favor of its benefits seems compellingly outsized in comparison. To the extent, though, that obfuscation can be conceptualized not just as a pricing strategy but as an ethically questionable practice, then there may also be less tangible "costs" that play a role in shaping outcomes. Shleifer (2004), for example, presents a framework (closely mirroring Gary Becker's 1957 discussion of discrimination) in which managers value ethical behavior, but "such behavior is a normal good." In other words, there is a *cost* to behaving ethically (i.e., not obfuscating), and firms will be less willing to bear this cost when their profits are squeezed. This actually fits quite well with many of the patterns of obfuscation that we observe in practice, and I expand more on this premise at various points throughout the following sections.

3.3.3 What Factors Might Moderate Incentives?

A range of variables may moderate the gains and costs to obfuscation discussed above. In this section, I outline several key factors – both at the market level, and at the firm level – that may play an important role.

Buyer Characteristics / Demand Conditions

While obfuscation can occur even in the absence of boundedly rational consumers (e.g., Carlin, 2009; Ellison and Ellison, 2009; Ellison and Wolitzky, 2010), the incentives to obfuscate should, arguably, rise with the proportion of "myopic" consumers in the market. Indeed, Gabaix and Laibson (2006) articulate this result formally, but it is also quite intuitive in a broader sense. If boundedly rational consumers are easily fooled by obfuscation, then the more of them there are in the market, the more tempting it is for any single firm to deviate from transparency to obfuscation in an effort to exploit these buyers. In practice, this suggests that we may observe less obfuscation in settings where the majority of buyers are savvy and/or experienced (e.g., in business-to-business transactions), and more in consumer-facing industries where buyers are unfamiliar with products/services and more easily confused to begin with.

Price sensitivity of buyers may also play an important role. Intuitively, if buyers are very sensitive to small changes in (advertised) price, then a little bit of trickery goes a long way. In contrast, if firms compete primarily on dimensions other than price, then there will be substantially less upside associated with obfuscation, all else equal. In some sense, price obfuscation can be thought of as a substitute for actually competing on *price*. This leads nicely into my next topic: competitive environment.

Competitive Environment

A number of the theory papers listed in in Section 3.2 make formal predictions regarding the relationship between competition and obfuscation, and the majority (Spiegler, 2006; Carlin, 2009, Chioveanu and Zhou, 2013) predict that price obfuscation will increase with the number of competitors in the market.[12] It is important to note, however, that in all three of these papers, obfuscation is assumed to result in consumer confusion (or uncertainty) about prices. This is markedly different from obfuscation that is designed to make prices look artificially low, and in the latter case, it is not clear that these formally derived predictions about the relationship between competition and obfuscation will apply.

However, if we return to the notion that managers may prefer to avoid obfuscation for ethical reasons, Shleifer's (2004) framework offers a clear prediction: obfuscation should increase with competitive pressure. As competition grows more intense, managers' demand for ethical behavior will fall, "leading to the spread of censured practices." In other words, as profits become more difficult to capture, firms become more willing to engage in ethically questionable practices that either lower costs or increase revenues. This basic intuition seems quite plausible in many settings, and several empirical papers provide evidence for the relevance of this perspective. Cai et al. (2005) find that firms in more competitive markets are more likely to engage in profit-hiding (i.e., tax evasion). In a study of the liver transplant industry, Snyder (2010) finds that transplant centers' propensity to manipulate the waiting list is higher in markets with multiple competitors. Bennett et al. (2013) study the vehicle emissions market and find that competition increases inspection leniency: "firm misconduct appears to increase with competitive pressure and the threat of losing customers to rival firms." Mayzlin et al. (2014) and Luca and Zervas (2015) both present evidence that firms (hotels and restaurants, respectively) in more competitive markets are more likely to receive fake negative reviews – ostensibly written by rival firms. And with regard to price obfuscation specifically, Chiles (2017) finds evidence that firms are more likely to shroud mandatory surcharges as the number of competitors that they face increases.

There are also other factors besides the number of firms in the market that may influence competitive conditions. The nature of competition may matter quite a lot (in particular, the extent to which firms compete on price, as discussed in the previous section). In addition,

[12] An outlier here is Wenzel (2014), who actually predicts that obfuscation will become less prevalent as the number of competitors increases.

worsening industry conditions may make rivalry more intense. Shleifer's (2004) framework can again be applied here: as profits are squeezed, managers will be more willing to engage in obfuscation. Indeed, the case studies in the following section provide several examples of price obfuscation proliferating in conjunction with a severe economic downturn.

Finally, the relevance of strategic interactions *between* competitors is important to consider. When obfuscation occurs in the form of trickery – i.e., presenting prices in a way that make them appear misleadingly low – a race to the bottom seems inevitable. In other words, if one firm begins to obfuscate in this manner, "in a way reminiscent of a price war . . . others will feel that they have no choice but to follow suit" (Nalebuff and Ayres (2003). If obfuscation is focused on making prices more confusing or unclear, the way in which one firm's decision might influence another's is a bit less obvious, and may depend to some extent on firm characteristics. For example, Grubb (2015) observes that in this type of situation, a firm with a cost advantage may be more likely to embrace transparency in the face of rivals' obfuscation, as it will win on price if it can facilitate accurate comparisons.

Technology

Technology likely cuts both ways in terms of its effect on firms' propensity to obfuscate. On the one hand, technology (via the internet) has dramatically reduced search frictions (e.g., Brown and Goolsbee, 2002), making prices much easier for consumers to compare. For firms, a key consequence of this is the heightening of competitive intensity, and, in particular, an increasing urgency to compete on (advertised) *price*. Hence, if competition increases firms' propensity to obfuscate (see discussion in the preceding section), then technologies such as the internet that spur more intense competition will also likely increase obfuscation efforts. Ellison and Wolitzky's (2012) model predicts this very result: decreases in exogenous search costs don't actually end up reducing prices, because they are fully offset by efforts to obfuscate.

On the other hand, the internet has also provided consumers with many more vehicles to *punish* firms for obfuscation (and other forms of bad behavior). Online review sites such as

Yelp and TripAdvisor allow consumers to leave feedback, informing other potential buyers about objectionable firm conduct. (Chiles (2017) finds evidence that hotel customers do, indeed, punish firms who obfuscate in their subsequent reviews.) More generally, social media outlets such as Twitter and Facebook are powerful tools for quickly disseminating information. Recent examples (such as the forcible removal of a United Airlines passenger from a flight) illustrate just how rapidly firms' bad behavior can "go viral" on these sites. Of course price obfuscation is very different from the violent removal of a passenger from a plane; in principle, however, the same sort of mechanism may apply on a smaller scale. On net, the role that technology plays in shaping firms' incentives to obfuscate is not at all clear – additional research is needed in this area.

Firm Characteristics

In Section 3.3.2, I discuss the various ways in which firms who obfuscate may incur reputational damage. At the firm-level, the relevance of this potential cost will matter more or less depending on the extent to which individual firms rely on their reputation (and the prospect of repeat business) as an important strategic asset. Chiles (2017), for example, finds that chain-affiliated hotels are less likely to charge shrouded "resort fees." The intuition is that if consumers punish all firms in the chain for one individual firm's obfuscation, then the cost of obfuscation is substantially larger. The reverse intuition applies in situations where firms are in financial distress or otherwise at risk of exit – reputation has little value to a firm that assigns a low probability to its existence in the future. This seems roughly in line with Shleifer's (2004) logic applied at the firm-level (rather than the market-level): firms that are underperforming their competitors may be more likely to resort to obfuscation in an effort to catch up. By contrast, Gu and Wenzel (2013), outline a theoretical model in which more "prominent" firms are *more* likely to obfuscate. Their key assumption in deriving this result is that confused consumers will be more likely to purchase from prominent firms – which does, indeed, seem plausible.

There are a host of other ways in which firm-level characteristics may influence incentives to engage in price obfuscation, and ultimately the way this play out in practice depends not just on the characteristics of the firm, but the way in which a firm's strategy and positioning *intersect* with market-level factors that affect the attractiveness of obfuscation. The case studies in the following section expand on this premise.

3.4 Strategic Transparency: When Does It Actually Work?

Ayres and Nalebuff (2003) argue that, "companies that engage in honest pricing can enjoy important benefits – happier customers, clearer product differentiation, and, consequently, higher profits. In short, telling people what things really cost can make more business sense than racing downward against competitors to an artificially low price." While their argument is certainly noble in its intent, it seems naively aspirational in light of the empirical reality that many attempts on the part of firms to do just this have been decisive failures. In the following sections, I examine cases from four unique industry settings where individual firms employ what I will refer to as "strategic transparency" (i.e., the implementation of transparent pricing policies in the face of industry-wide obfuscation). For two of the firms discussed (Caesars Entertainment and StubHub), strategic transparency proved to be a losing proposition. Other firms (CarMax and Southwest) have arguably achieved success in this pursuit. Throughout this discussion, I summarize key distinctions between these case studies in success and failure. In particular, in the instances where strategic transparency succeeds, I hone in on the critical way in which firms' strategy and positioning interact with market-level incentives to obfuscate.

3.4.1 Caesars Entertainment

Most travelers have (unhappily) encountered shrouded charges in the hotel industry at some point or another. In addition to fees for avoidable add-ons such as WiFi, parking, late check-out, etc., mandatory surcharges – typically dubbed "resort fees" – are also fairly common. As of April 2017, resort fees were imposed by roughly 6-7% of hotels in the U.S., but in Las Vegas, this figure spikes to more than 50%. On the Strip[13] itself, 100% of hotels charge these fees (Chiles, 2017). While resort fees have been around for many years, their widespread proliferation in Las Vegas is a relatively recent phenomenon, tracing back to 2009. The Great Recession hit the hotel industry hard, and hotels in Las Vegas were particularly impacted. Schwartz (2013) writes that, "at the height of the recession, resort fees seemed like a boon to casino executives bedeviled by falling revenue." In the second half of 2009, MGM Mirage (which in 2009 owned roughly one third of the 28 hotels on the Las Vegas Strip) began implementing resort fees at its lower-end properties. Independent hotels such as Treasure Island and the Venetian/Palazzo also adopted around this time. The Wynn/Encore followed in mid-2010 (Finnegan, 2010), and by the end of 2010, MGM Mirage decided to roll out resort fees at *all* of its Strip properties, including the high-end Bellagio (Benston, 2010).

Caesars Entertainment held out. With eight properties, Caesars roughly equalled MGM Mirage in terms of presence on the Strip. And it was gambling on the belief that travelers would hate its competitors' hidden fees so much that they would ultimately be driven away. "I don't think people will get used to paying these fees. We follow what our competitors are doing . . . and we have witnessed some unpleasant conversations in their lobbies," claimed Vice President of Marketing Michael Weaver in mid-2010 (Benston, 2010). And, indeed, travelers despised the new resort fees, which also received unfavorable media coverage and scrutiny from consumer groups. Caesars acted to capitalize on this negative sentiment. They started a Facebook group (joined by more than ten thousand users) rallying consumers to "fight against Las Vegas resort fees" (Pawlowski, 2013). They prominently advertised "no resort fees" on all property websites and on large billboards outside their casinos (Finnegan, 2010). They even hired showgirls to march in protest parades down the Strip, waving signs with slogans like "just say no to resort fees!" (See Figure 3.1.)

Suddenly, in 2013, Caesars dramatically reversed course, announcing that they would implement resort fees at all eight of their properties on the Strip. While official statements only made vague references to the "current industry standard in the market" (Sylvester,

[13] "The Strip" in Las Vegas is an area known for its concentration of casinos.

Figure 3.1: "Resort Fees Should Be a Choice!"

Source: Las Vegas Sun (Sylvester, 2013); photo taken in 2011

2013), there can be little doubt that competitive pressure was a critical factor in the decision. Competitors' implementation of resort fees allowed their properties to effectively advertise (misleadingly) lower room rates – in all settings, but perhaps most importantly on travel websites such as Expedia commonly used by consumers to compare (base) prices across hotels. In these comparisons, Caesars' properties now appeared less competitive next to the artificially low prices advertised by resort-fee-charging rivals. Indeed, a University of Nevada (Las Vegas) survey found that 88% of travelers to the Strip did not consider resort fees when choosing a hotel (Sylvester, 2013). In other words, while travelers might have disliked resort fees, they simply failed to account for them when selecting a property. And while some travelers did gripe about resort fees at checkout or in online reviews, the impact of this sort of pushback was trivial in comparison to the revenue gains at stake in this setting. Fundamentally, nothing about Caesars' strategy or competitive position insulated it from these powerful market forces. Other than its attempt to embrace transparent pricing, it was largely pursuing the same sort of customers through the same set of channels with the same type of strategy as its competitors. Because of this, its efforts at transparency were likely destined for failure from the start.

Today, resort fees in Las Vegas are more rampant than ever. They have spread from the Strip to other areas of the city (indeed, they are increasing in prevalence in many metropolitan areas across the country). Moreover, on the Strip, the average *magnitude* of resort fees continues to grow at an astonishing rate. In early 2013, no hotel on the Las Vegas Strip charged a fee of more than \$25, and many were lower, in the \$10-\$15 range. By April 2015, the *average* resort fee charge on the Strip was \$26, and by April 2017, this number had climbed to \$39 (Chiles, 2017). In addition, many of these hotels have also begun to charge separately for parking (Sachs, 2017), a perk previously "included" in the resort fee charge. As one reviewer on TripAdvisor cynically commented, "I'm waiting for the day when rooms are advertised for \$5, and all the rest is [charged] in hidden fees." Indeed, firms in this setting seem trapped in a war of obfuscation, with no apparent end in sight.

3.4.2 CarMax

In the *Handbook on the Economics of Retailing and Distribution* (Basker, 2016), Sara Fisher Ellison begins her chapter on price obfuscation by describing the process of shopping for a car. In this setting, local dealerships engage in a wide array of tactics seemingly intended to frustrate search. For one, prices are "fuzzy" in the sense that they are negotiable – the posted price (if there is a posted price) is not what buyers typically end up paying. And once a potential buyer enters negotiations, dealers often draw out the sales process unnecessarily. As Ellison puts it, buying a car tends to "involve a fair amount of sitting around" (often several hours in total). These tactics make it quite laborious for buyers to visit multiple firms for the purpose of price comparisons. In addition, many firms charge mandatory fees (e.g., "dealer fees") that are shrouded until buyers reach the final stage of the purchase process. And at least historically, dealers have been notorious for engaging in bait and switch. Here, firms advertise one model at a very low price to draw buyers onto their lot. Once buyers reach the lot, however, they find that this low-priced model is actually "out of stock." Dealers then attempt to market higher-priced cars to these (now captive) potential buyers.

These sorts of obfuscation tactics were rampant in the market for used cars that CarMax entered in 1993. Now the largest used car retailer in the U.S., CarMax began with just a few locations throughout the southeast. From the start, their approach was radically different from that of incumbent automotive dealers along several important dimensions, including, notably, an embrace of transparent pricing. Instead of engaging in the obfuscation tactics described above, CarMax espoused a "no-haggle" approach. Sticker prices (listed clearly both online and in store) were fixed rather than negotiable. This negated any need for the protracted back-and-forth stalling tactics commonly employed by traditional dealers. On the lot, buyers could easily search and compare inventory via electronic kiosks. Sales consultants – paid a flat commission on every vehicle sold – had no incentive to engage in aggressive upselling tactics. Once a buyer was ready to purchase, the process was structured and efficient.

Figure 3.2: "We Would NEVER Sell You This Car"

Source: CarMax website

CarMax also differed from traditional dealers in some other key ways. For one, their stores offered a substantially larger selection of inventory. Each location carried 300-500 cars – four to five times more than the average dealer – and this inventory was carefully matched to meet demand in specific geographies. "The Houston store, for instance, had more trucks than the suburban DC store, which in turn had more luxury cars than the Houston location" (Lal and Kiron, 2005).[14] CarMax also focused on building consumers' trust (which in the used car market, had historically been a challenge). Vehicles were reconditioned via a rigorous process and backed by generous customer return policies. The company's messaging focused on its commitment to screening out "lemons:" every showroom featured a display vehicle that had been refurbished (to look new) after having sustained structural damage. The display car would always be accompanied by a photo of what it had looked like before reconditioning, as well as prominent signage informing customers that CarMax would never sell such a car (see Figure 3.2). In addition to touting CarMax's quality and trustworthiness, this sort of message also served (not so subtly) as a warning to consumers about the risks of buying a used car elsewhere.

In light of the difficulties that Caesars (see the preceeding Section 3.4.1) faced in its attempts to differentiate via price transparency, it seems fair to question whether or not CarMax's strategy was wise in this regard. Indeed, a Senior VP of marketing and strategy for CarMax recalls analysts raising this very question when the company went public in 1997:

> *One of the big analyst fears was that a consumer could go to the showroom and in 15 minutes get the price of a car they are interested in. The analysts argued, "What consumer isn't going to see if they can get a lower price somewhere else? The first dealer they walk to will always give them a lower price, if they come in saying 'This is what CarMax is selling this kind of car for.' Dealers are going to kill you every time because any customer who price shops can always get a lower price."*
>
> \- **Joe Kunkel, Senior VP of Marketing and Strategy** (1997)[15]

These concerns proved unfounded. By 2001, CarMax's gross profit margins (including financing) were 15.1% compared with 13.4% on average at traditional dealerships (Lal and Kiron, 2005). And they have continued to grow steadily, reaching $15 billion in revenue in 2016 – all the while, never wavering in their commitment to price transparency. So why

[14] This ability to effectively match inventory to market demand was built upon a $65 million IT system to support sophisticated analytics as well as years of retail expertise leveraged from Carmax's parent company, Circuit City (Lal and Kiron, 2005).

[15] *Quoted in Lal and Kiron, 2005.*

was CarMax successful where Caesars failed? At a fundamental level, the first thing that is important to observe here is that CarMax's strategy differed substantially from that of its competitors, whereas Caesars' did not. A theme that will repeat itself throughout subsequent case studies as well is that price transparency *alone* does not tend to be an effective form of differentiation in the face of market-level pressures to obfuscate. Unless a firm's advantage or position within its industry is sufficiently different from that of its competitors, it is unlikely that it will be able to effectively leverage strategic transparency as a competitive weapon.

In this case, CarMax's pursuit of price transparency was part of a larger value proposition built around trustworthiness (as sketched above). Trust mattered *tremendously* in the used car market, and transparent pricing reinforced this trust, whereas obfuscation might have weakened it as a means of differentiation. A second key piece of the puzzle has to do with CarMax's decision to build large superstores with vast on-lot inventories. Traditional dealers' elaborate obfuscation tactics were primarily aimed at preventing consumers from shopping around. And, indeed, these tactics tended to be highly successful: consumers were so worn down by the sales process at traditional dealerships that roughly a third bought at the first shop they visited (Lal and Kiron, 2005). With CarMax, these gratuitous search costs were removed – precisely the concern articulated by analysts in 1997. But because CarMax offered such a large selection, buyers didn't *need* to shop around at other dealerships; they were able to compare a wide range of options from among Carmax's vast on-site inventory.[16] This dynamic was further reinforced through CarMax's reputation for trustworthiness: buyers who trust that they are being offered a fair price will naturally be less inclined to price shop. Here, transparent pricing reinforced CarMax's strategy, and CarMax's strategy, correspondingly, reinforced its ability to offer transparent pricing (as their competitive position in the market rendered obfuscation unnecessary). End to end, strategic transparency has served a critical role in CarMax's success.

[16] As Kunkel explained: "If you want to compare a 1998 Camry, a 1998 Accord, and a 2000 Taurus, you probably have to go to three dealership to find the exact car that you want. In our case, you can do that all on one lot." (Lal and Kiron, 2005)

3.4.3 StubHub

Shrouded service fees are a pain point for consumers who purchase tickets online. Most platforms charge some version of these fees, which are typically tacked on just before checkout. StubHub (the largest online ticket reseller in the U.S.), has attracted particularly negative criticism for its fees, which today, at $15-$17 per ticket (on the buyer side), are considerably higher than the fees on most other platforms. In 2014, however, StubHub famously moved to appease customers by moving to more transparent "all-in" pricing. When it suddenly reversed course the following year (reverting back to its original fee structure), it was revealed that the switch to transparent pricing had resulted in a dramatic drop in sales. What led StubHub to attempt transparent pricing, and why did it fail?

In the period leading up to 2014, StubHub commanded a substantial share of ticket sales in the secondary market. Estimates differed as to the precise figure,[17] but most put StubHub at upwards of 30% and some as high as 70% – in any scenario, substantially more than any other firm in the industry. But it was facing increasing competition from rivals both new and old. A fresh set of entrants (e.g., SeatGeek and TicketIQ) sought to aggregate ticket resale listings from multiple platforms into one consolidated location – similar to the way in which Kayak aggregates flight data (Grobart, 2012). Upstart resale platforms such as TickPick (founded in 2011) were touting new technology and undercutting StubHub on fees. Most notably, though, the dominant player in primary ticket sales, Ticketmaster, was launching a new foray into the secondary market.

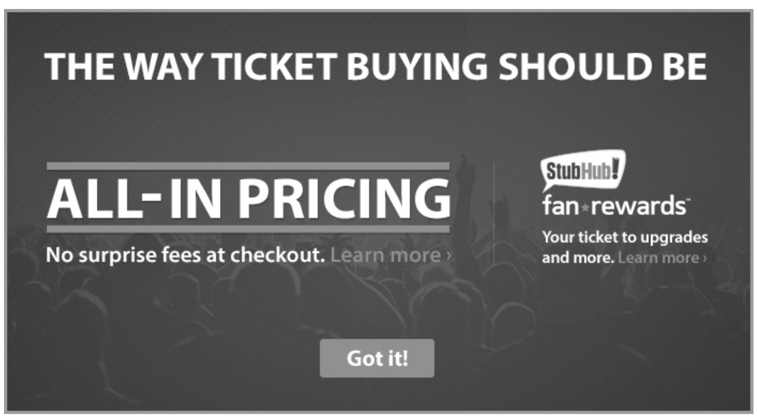
The TM+ platform, which launched in summer 2013, allowed buyers to view primary and secondary ticket listings on a single event page (Fisher, 2013).[18] Though initially focused on tickets for professional sporting events, the TM+ platform was also in testing for musical

[17]For the most part, these disparities are due to differences in how the secondary ticket market itself is defined.

[18]TM+ was different from StubHub in that it did not allow third parties to list directly on the site – rather, it operated by pulling in data on resale listings from the Ticketmaster-supported TeamExchange sites and TicketsNow platform. So its resale ticket listings were, perhaps, less comprehensive than StubHub's, but the combination of the primary and secondary market listings *together* offered buyers substantially more selection in many cases.

events by December of that year, and the company planned to roll it out more broadly by the summer of 2014 – in time for peak concert season. This move marked a major shift in the competitive dynamic between StubHub and Ticketmaster. Historically, Ticketmaster and StubHub had largely competed in separate segments of the market: StubHub led in ticket resale, while Ticketmaster focused on the primary market, cultivating a wide swath of exclusive relationships with event venues. Would StubHub's buyers (and subsequently, sellers) flee the platform if they could now find *both* primary and secondary listings in the same place on TM+? Financial details regarding the initial success of the TM+ platform were not disclosed, but Ticketmaster did note publicly that sales conversion rates were roughly 50% higher for events where buyers were able to view both primary and secondary ticket options simultaneously (Fisher, 2013). Hoping to stem the tide, StubHub turned to a tactic that they hoped would keep their buyers happy: all-in pricing.

Figure 3.3: "The Way Ticket Buying Should Be"



Source: StubHub website

StubHub first announced its shift to all-in pricing in January 2014 with a new slogan: "the way ticket buying should be." Importantly, all-in pricing didn't mean that StubHub would get rid of their fees, but rather that they would roll them into the up-front price displayed to consumers. This transparency would eliminate the unpleasant surprise at check-out that buyers had grown to hate. Following the switch, customers did, indeed, seem pleased: StubHub was quick to cite significant increases in customer satisfaction (Angulo, 2014), and the move was also met with positive media coverage and praise from consumer groups. Cracks began to appear, though, as early as March, when the Wall Street Journal reported that fans were gravitating toward other ticket resale sites, as StubHub's all-in price made its tickets appear more expensive (Karp, 2014). StubHub, apparently, had counted on competitors' following its move and adopting greater transparency themselves, but this did not materialize; instead, rivals who continued to utilize low advertised prices and high hidden surcharges now looked like a much better deal to inattentive consumers. Professional ticket brokers (agents who listed large volumes of tickets on StubHub) reported sales declines of as much as 50% (Smith, 2015).

Initially, rather than backing away from all-in pricing, StubHub actually went one step further and began to slash fees. It reduced buyer fees dramatically (from 10% of base ticket price to as little as 2% on some transactions) and also made concessions to fees on the seller side (Karp, 2014). This proved to be effective in mitigating declines in volume, but resulted in what eBay CFO Robert Swan[19] referred to as "a material deceleration" in StubHub's revenues and profitability. Finally in August 2015, StubHub pulled the plug, reverting to its original method of shrouding service fees until check-out. The deciding factor seems to have been a brief experiment in which the company randomized the price format that a customer would receive. Some customers were shown an all-in price, and some were shown a low base price, with surcharges added only at check-out. The outcome disparity was stark and immediate: demand was higher with shrouded surcharges, a difference that StubHub's new president, Scott Cutler, said was apparent "within the first hour of the data starting to come in . . . customers may say they crave greater price transparency, but their buying habits don't show it" (Smith, 2015).

It is interesting to consider whether or not StubHub's attempt at transparent pricing might have ended differently if the company had pursued this approach from the beginning. StubHub effectively created the market for online ticket resale, and was the only major player in this space for years. In this sense, they had considerable power to shape industry norms.

[19]eBay acquired StubHub in 2007.

Had they pursued transparent pricing from the start, perhaps they may have prevailed. There is compelling reason, however, to be skeptical of this view. Like Caesars (and in contrast to CarMax), there was never anything fundamental about StubHub's strategy or positioning that might have insulated it from market-level pressures to obfuscate (which seem particularly intense in this setting). If StubHub hadn't been the first to utilize shrouded surcharges, a competitor would have almost certainly beaten them to it and, eventually, dragged the rest of the industry along as well.

3.4.4 Airlines: The Case of Baggage Fees

Over the past several years there has been a steady stream of headlines concerning airline surcharges, which today include a wide range of avoidable add-ons – checked bags, carry-on bags, snacks/drinks, advance seating assignments, and even paper boarding passes. As with hotels (see Section 3.4.1), this proliferation of fees is a relatively new phenomenon and can be traced back to the Great Recession. Checked bags fees are one of the more widespread examples, and are the primary focus of my discussion here. Before beginning, though, it is fair to first ask: are these sorts of avoidable surcharges really price obfuscation at all? Because they are for goods and services that are optional, the answer is not immediately clear – perhaps these changes in price structure are best viewed as unbundling rather than obfuscation. A rather damning counterargument, however, is that the airline industry has fought hard against policies that would require them to disclose surcharges more transparently.[20] That the airlines themselves are so reticent to make surcharges for add-ons more salient seems to imply that there is at least some element of obfuscation inherent in these practices.

Low-cost carriers Spirit and Allegiant were the first to start charging for checked bags in 2007. At the time, this move was considered rather bizarre. "Spirit Airlines said Tuesday it will take the unusual step of charging for all checked baggage ..." begins the Associated

[20] At several points over the last several years, the Department of Transportation has contemplated instituting rules that would require fees for ancillary services to be listed beside fares at all points during the booking process. The trade group Airlines for America has fought repeatedly against these measures. (Silk, 2017)

Press story covering the announcement (Sainz, 2007). In the same article, travel consultants confidently predicted that "you wouldn't see a lemming type of match from the larger carriers." Of course, they were wrong. American Airlines was the first legacy carrier to announce the addition of checked bag fees (in May 2008). United and US Airways followed within weeks (Maynard, 2008), as did Delta and most other carriers by the end of 2008. Only two carriers held out: Southwest and JetBlue. Over the next several years, bag fees increased in magnitude (from \$15 per leg in 2008 for most carriers to \$25 per leg by 2014). In 2010, Spirit upped the ante even further with new fees for *carry-on* bags. Baggage fees alone contributed more than \$3.5 billion in revenue to airlines by 2014,[21] and were viewed as a tremendous boon to industry profitability. When JetBlue announced in 2015 that it, too, would begin to collect fees for checked bags, consumers might have been livid – but investors were pleased (Dastin, 2015).

Figure 3.4: "Bags Fly Free"

Source: Southwest Airlines

Southwest, in contrast, has embraced its position as the only remaining carrier to offer free checked bags, prominently heralding a "bags fly free" slogan in their marketing and even physically on their planes. Yet unlike Caesars, which ultimately succumbed to market

[21] Bureau of Transportation Statistics

pressures and adopted hidden fees, Southwest's defiant stand for price transparency appears to be working (at least so far). Why has Southwest been able to succeed here, while JetBlue – for years the only other holdout – was ultimately not? In answering this question, it is important to first understand how *else* Southwest is different from its competitors.

Perhaps most notably, Southwest is unique in the airline industry in not allowing its flights to be listed on OTAs and other aggregation sites like Kayak. The origins of this policy can be traced back to Southwest's beginnings. Always operating with an eye towards cost savings, Southwest was far ahead of the curve in moving its ticket sales online – where it could avoid expensive travel agent commissions. In the first quarter of 1999, for example, more than 25% of the carrier's ticket sales were from bookings on its website, compared with about 5% for United (McDowell, 2000). However, over the next several years, as other airlines began to increasingly accept the necessity of online travel agents (e.g., Expedia), Southwest refused, citing a desire to maintain control and avoid middleman expenses (Sandoval, 2002). Most major airlines serving mass markets would not have been able to afford to make such a decision. But Southwest's customers were focused in a smaller set of core markets, where the company had, by now, established a strong reputation for offering competitive prices. As an analyst from the travel market research firm Phocuswright put it, "they've always operated as a low-cost leader, so *people will hunt for them*" (Sandoval, 2002).

To this day, Southwest does not list its fares anywhere online except its own website, and herein may lie the key to the success of its transparent pricing. Similarly to Caesars Entertainment in the hotel industry (see Section 3.4.1), Southwest's competitors in the airline industry faced tremendous pressure to make base prices look as low as possible due to the ease with which consumers could compare fares across carriers on online travel sites. Southwest, by removing itself from the OTA distribution channel, also effectively removed much of this pressure. Many buyers go straight to Southwest.com and never look anywhere else, "because of the entrenched perception that Southwest's fares are lower than its competitors" (Winship, 2013).

As long as Southwest can continue to rely on this perception to drive buyers to its site, avoiding obfuscation is likely a smart strategy. This is a somewhat tenuous position, however, especially as Southwest's cost structure looks increasingly similar to that of the legacy carriers (Bachman, 2014). An airline whose cost advantage has eroded cannot continue to maintain a reputation for being a one-stop shop for low fares – consumers will notice, and the firm will, accordingly, have to make policy adjustments if buyers increase the extent to which they price shop Southwest against other carriers. Indeed, a widely circulated 2013 study found that Southwest offered the lowest fare on their routes only 35% of the time (Tuttle, 2013).[22] And recently, CEO Gary Kelly conceded that while Southwest would hold firm to its "bags fly free" policy (at least for now), it was actively exploring other forms of ancillary surcharges (Jansen, 2016). It will not be surprising if Southwest follows its competitors down this road eventually.

Figure 3.5: Former Spirit CEO Ben Baldanza Stuffs Himself Into an Overhead Bin

Source: Spirit Air

Spirit is a fascinating foil to Southwest in all of this. It has fully embraced (and, indeed, led) industry-level pressure to obfuscate fares with a proliferation of surcharges. Today, roughly

[22]In Southwest's defense, this study only compared base prices and did not take into account the difference in ancillary fee structures between Southwest and its competitors – which may account for quite a bit of the difference in this finding.

40% of Spirit's revenue comes from ancillary fees – a staggering amount in comparison with legacy carriers' 8% (Bender, 2014). At least some buyers clearly find Spirit's approach objectionable: the company consistently ranks dead last in passenger satisfaction surveys.[23] But its operating margins continue to be some of the highest in the industry. Clearly the company understood early on that consumers respond strongly to price in this market and that finding ways to offer the lowest base price possible could be a winning tack. Indeed, legacy carriers have followed Spirit time after time. Most recently, American and United have indicated that they will no longer include access to overhead bins in the price of their most basic ticket class (Zhang, 2017). These sorts of customer-hated policies require more of a balancing act from legacy carriers, who at least assert to maintain a focus on customer service. In contrast, Spirit has unabashedly leaned into its image as the industry's "bad boy," with (until recently) a brash, quirky CEO, a tawdry approach to marketing, and zero apologies. Perhaps there is a lesson here: if industry-level incentives to obfuscate are intense, then he who obfuscates best may, in fact, win.

3.5 Conclusions

In this chapter, I focus on forwarding our understanding of why, in practice, some firms engage in price obfuscation and others do not. Many papers have yielded important insights with regard to the conditions under which obfuscation will tend to flourish. On net, however, this question has not been a primary focus of the literature to date. To this end, I draw from both existing research and from industry case studies to paint a fuller picture of the factors that may be central in influencing outcomes.

Importantly, obfuscation tactics can suppress price information in two fundamental ways: they can be designed to make prices appear misleadingly low, or they can be designed to create general confusion or uncertainty about prices (in no particular direction). In both instances, the preponderance of evidence (both theoretical and empirical) suggests that the

[23] American Customer Satisfaction Index, 2017

financial gains for firms are quite substantial. These gains may be moderated, however, by a range of factors at both the firm and market level. At the market level, one factor that stands out as particularly important is the role of competitive pressure. In both the theoretical and empirical literature (and in two of the four industry case studies – hotels and airlines), the prevalence of obfuscation increases as the number of competitors in the market grows and/or as industry conditions deteriorate, intensifying rivalry. There are various intuitions for this relationship, but a compelling one (that seems to fit particularly well with what we observe in practice) is that managers are more willing to engage in ethically questionable practices such as obfuscation (that they would otherwise prefer to avoid) when their ability to capture profit is constrained by competitive industry conditions.

Perhaps the most important conclusion to draw from the collection of four case studies presented here is that attempts at strategic transparency are not likely to succeed in a vacuum. In particular, firms seem to frequently overestimate the extent to which consumers value transparency versus the extent to which they will be swayed by a (misleadingly) low price. And on net, firms that pursue transparent pricing in the face of market-level pressures to obfuscate seem to fail in this endeavor much more often than not. The ones who succeed (e.g., CarMax, Southwest) are positioned strategically such that they are largely insulated from these market-level pressures. When this condition holds, transparency can potentially be a powerful competitive weapon precisely because rivals (who remain mired by the competitive pressure to obfuscate) will be unable to imitate.

In contemplating important directions for future research, a recurring motif in case studies is the role of the internet as a critical determinant of competitive intensity. Yet the role of the internet in shaping obfuscation outcomes is not entirely clear-cut, as the internet likely increases both the pressure to obfuscate and the potential costs of obfuscation. More research is needed to understand how these two effects net out in practice. The empirical literature also has very little to say about the extent to which firms pursue obfuscation as a substitute for activities that actually create value (i.e., efforts to lower costs, to innovate, etc.). Certainly the prevailing view is that obfuscation is socially unproductive, but the emphasis to date has been on how obfuscation hurts consumers via higher prices and/or higher search costs. The social loss may be even greater to the extent that firms obfuscate in lieu of more productive activities. This is certainly worth exploring more. Finally, there remains a puzzling imbalance between what we know about the potential financial gains to obfuscation (which seem quite large) versus what we know about the potential costs (which seem quite modest in comparison). Given this disparity, it is surprising, perhaps, that we do not observe obfuscation occurring more universally in practice. Perhaps managers' ethical preferences are an important factor to consider here. Perhaps the large financial gains that are often observed in experimental settings dissipate over time when obfuscation tactics are implemented by firms in the real world. Or perhaps we are headed towards a new equilibrium where obfuscation is, indeed, more universally adopted by firms. If this is the case, then an understanding of these issues is especially critical.

Appendix: Additional Tables

Table A1: Key Variable Definitions (Chapter 1)

Variable	***Description***
hotel_comps	The number of firms with which a given hotel competes in its corresponding ZIP-5 market (if a hotel is the only firm in its market, this variable equals zero), measured in units of ten. Varies across time.
vrs:	The number of vacation rental listings on TripAdvisor that correspond to a hotel's ZIP-5 market, measured in hundreds. Varies across time.
pc_comps_rfee:	The percent of a hotel's competitors that charge resort fees. If a hotel has no competitors (*hotel_comps* = 0), this value is set to zero; a dummy variable for whether or not a hotel has any competitors (*any_comps*, described below) is included in all regressions to account for the treatment of these missing values. Varies across time.
pc_comps_wifich:	The percent of a hotel's competitors that charge for WiFi. See above for treatment if (*hotel_comps* = 0). Varies across time.
stars:	The star category assigned to each individual hotel by Expedia. Properties can receive scores between 1 and 5 in half-star increments, which reflect the level of accommodations/services that the hotel offers. Varies across time.
rooms:	The total number of rooms at a given hotel as listed by Hotels.com. (To be clear, this metric reflects the total number of rooms at a property – *not* the number of rooms that are available for booking (i.e., unreserved) at a specific point in time.) Varies across time.
chain:	A dummy variable equal to 1 if the property is affiliated with a major hotel chain (see Table A4 for a list of chains included in the calculation of this variable). Varies across time.
roomshare:	Number of rooms at a given property divided by the total number of rooms in the ZIP-5 market. Varies across time.
any_comps:	A dummy variable equal to 1 if a hotel has any competitors and equal to 0 if it is the only firm in its market. (See *pc_comps_resort_fee* and *pc_comps_wifi_fee* for more details on how this variable is used.)
pc_comps_chain:	The percent of a hotel's competitors that are chain-affiliated. See *pc_comps_rfee* for treatment if (*hotel_comps* = 0). Varies across time.
seasonality:	Monthly enplanements (for all hubs within 50 miles of corresponding hotel) for peak month (2015) divided by monthly enplanements for lowest month (2015). For example, if a hub receives one million enplanements in its peak month and 200,000 enplanements its lowest month, this ratio will equal 5. Time invariant.
pc_business:	For a hotel's corresponding ZIP-5 market, the percent of reviewers (on TripAdvisor) who identify as business travelers. Time invariant.
pc_english:	For a hotel's corresponding ZIP-5 market, the percent of reviews (on TripAdvisor) written in English. Time invariant.
chain_rfee_iv:	For each chain-affiliated competitor in market j, average resort fee utilization rate for the corresponding chain in markets $-j$ is computed. This statistic is then averaged over all chain-affiliated competitors in market j.
chain_wifi_iv:	For each chain-affiliated competitor in market j, average WiFi surcharge utilization rate for the corresponding chain in markets $-j$ is computed. This statistic is then averaged over all chain-affiliated competitors in market j.

Table A2: Key Variable Definitions (Chapter 2)

Variable	*Description*
avg_rating	The average cumulative traveler rating for a hotel, on a scale of 1 to 5 (displayed in increments of 0.1 points). Average ratings reflect traveler reviews written on Hotels.com and Expedia.com beginning in 2012. These reviews are submitted *only* by individuals who booked through an Expedia platform.
resort_fee_sep:	A dummy variable, equal to 1 if the hotel charges a resort fee that is *not* included in the total price paid up front by Hotels.com/Expedia customers.
resort_fee_inc:	A dummy variable, equal to 1 if the hotel charges a resort fee that *is* included in the total price paid up front by Hotels.com/Expedia customers.
stars:	The star category assigned to each individual hotel by Expedia. Properties can receive scores between 1 and 5 in half-star increments, which reflect the level of accommodations and services that the hotel offers. It is important to distinguish between a hotel's star categorization and its average traveler rating; while higher-star hotels do tend to receive higher traveler ratings on average, it is possible for a 2-star hotel to have very high traveler ratings, while a 4-star hotel might receive low ratings.
resort_amenities	A dummy variable, equal to 1 if the hotel features at least one of the following "resort amenities:" *beach_pool_amenities=1*, *fitness_classes=1*, *fitness= "Health Club On Site"*, *spa=Full-Service Spa On Site"*, *golf_onsite =1*.
major_chain:	A dummy variable equal to 1 if the property is affiliated with a major hotel chain (see Table A4 for a list of chains included in the calculation of this variable).
log_price:	The natural log of the lowest nightly rate displayed on each hotel's main Hotels.com page. This nightly price may correspond to any date within two weeks of the date on which the page was referenced. In all cases, this price reflects only the base rate (and does *not* include the amount of the resort fee).
log_rooms:	The natural log of the total number of rooms at a given hotel as listed by Hotels.com.[24]
optional_fees:	Dummy variables indicate whether or not a hotel charges for the following optional add-ons: wireless internet in the guest rooms (*wifi_fee*), self-parking (*selfpark_fee*), late check-out (*latechk_fee*), and infant cribs (*crib_fee*). The variable *optional_fees* is the sum of these dummy variables. It reflects the number of optional add-on fees a hotel charges out of these four major categories.

Table A3: Descriptions for Detailed Controls (Chapter 2)

Variable(s)	***Description***
water_onsite, winter_onsite	Dummy variables indicating whether or not a hotel offers (respectively) water activities (e.g., surfing, sailing, snorkeling, etc.) and winter activities (e.g., skiing, sledding, etc.) on site.
tennis_onsite, golf_onsite	Dummy variables indicating whether or not a hotel offers (respectively) tennis and golf on site.
casino	Dummy variable indicating whether or not a hotel has a casino on site.
fitness	Categorical variable indicating the type of fitness facilities a hotel property offers. Possible values include: "None," "24-Hour Fitness Facilities On Site," "Fitness Facilities (Hours Vary) On Site," "Health Club On Site," and "Use of Nearby Fitness Center."
fitness_classes	Dummy variable indicating whether or not a hotel offers fitness classes.
spa	Categorical variable indicating spa services offered by a hotel property. Possible values include: "None," "Full-Service Spa On Site," and "Spa Services / Spa Treatment Rooms On Site."
restaurants	The number of restaurants that a hotel property offers on site.
roomserv	Categorical variable indicating the type of room service a hotel property offers. Possible values include: "None," "Room Service (Limited Hours)," and "24-Hour Room Service."
concierge	Dummy variable indicating whether or not a hotel offers concierge service.
turndown	Dummy variable indicating whether or not a hotel offers turndown service.
indoor_pools, outdoor_pools	The number of (respectively) indoor and outdoor pools a hotel offers.
beach_pool_amenities	Dummy variable indicating whether or not a hotel offers beach and/or pool services (e.g., loungers, towels, cabanas, etc.).

Table A4: Major Chains

The variable *chain* is equal to 1 if a hotel is affiliated with any of these chains. This list also corresponds to the chain-level categorization used in the construction of the instrumental variable in Section 1.4.2.

Group	***Chains Included***
Best Western Hotel Group:	Best Western, Best Western Plus, Best Western Premier
Carlson Rezidor Hotel Group:	Country Inn & Suites, Park Inn by Radisson, Park Plaza, Radisson, Radisson Blu
Choice Hotels:	Ascend, Cambria, Clarion, Comfort Inn (& Suites), Econolodge, Mainstay, Quality Inn (& Suites), Rodeway, Sleep Inn, Suburban Extended Stay
Hilton Worldwide:	Conrad, DoubleTree, Embassy Suites, Hampton Inn (& Suites), Hilton, Hilton Garden Inn, Home2, Homewood, Waldorf Astoria
Hyatt Hotels Corp:	Andaz, Grand Hyatt, Hyatt, Hyatt House, Hyatt Place, Hyatt Regency, Park Hyatt
InterContinental Hotels Group:	Candlewood, Crowne Plaza, EVEN Hotel, Holiday Inn, Holiday Inn Express, Hotel Indigo, InterContinental, Kimpton, Staybridge
La Quinta:	La Quinta
Marriott International:	Autograph Collection, Courtyard by Marriott, Fairfield, Gaylord, JW Marriott, Marriott, Renaissance, Residence, Ritz-Carlton, Springhill, Towneplace
Motel 6:	Motel 6, Studio 6
Starwood Hotels and Resorts:	Aloft, Element, Four Points, Le Meridien, Luxury Collection, Sheraton, St. Regis, W Hotels, Westin
Wyndham Worldwide:	Baymont Inn (& Suites), Days Inn (& Suites), Hawthorn Suites, Howard Johnson, Howard Johnson Express, Knights Inn, Microtel, Planet Hollywood, Ramada, Super 8, Travelodge, Tryp, Wingate by Wyndham, Wyndham, Wyndham Garden, Wyndham Grand

Table A5: Share of North American Transient Bookings by Channel

Channel	Q1 2015	Q2 2015	Q1 2016	Q2 2016
Hotel Websites	33.1%	33.6%	34.7%	35.3%
Hotel Direct[a]	24.2%	21.0%	22.1%	19.1%
Travel Agents	15.4%	15.2%	15.8%	15.8%
OTAs	14.0%	15.9%	14.9%	16.0%
CRO[b]	13.3%	14.3%	12.4%	13.8%

Note: "Transient" refers to individual leisure and business travelers
[a] *Includes direct calls to hotel properties and walk-in customers*
[b] *Central Reservation Offices (calls to a hotel chain's 800-number)*
Source: *TravelClick*

Table A6: Top Resort Fee Markets

Market	Total Hotels	% Charging Resort Fee	Avg. Resort Fee	Avg. Fee as % of Room Rate
Urban Honolulu, HI	100	49.0%	$18.47	10.4%
Myrtle Beach-Conway-N. Myrtle Beach, SC	212	48.6%	$11.22	6.9%
Breckenridge, CO	80	47.5%	$16.87	10.8%
Las Vegas-Henderson-Paradise, NV	232	47.4%	$21.10	28.0%
Crestview-Fort Walton Beach-Destin, FL	112	39.3%	$42.35	18.7%
Miami-Miami Beach-Kendall, FL	395	36.7%	$19.07	11.8%
Panama City, FL	100	36.0%	$24.15	11.3%
Key West, FL	153	33.3%	$20.18	8.5%
Kahului-Wailuku-Lahaina, HI	112	32.1%	$22.09	7.5%
Glenwood Springs, CO	78	33.3%	$19.10	6.5%
All Other Areas	39,012	5.4%	$15.56	10.3%
Overall	**40,586**	**6.8%**	**$16.73**	**10.7%**

Note: "Top markets" are defined as MSAs with $\geq$ 75 hotels where at least 30% of properties charge resort fees.

Table A7: Resort Fee Trends by Star Category in the U.S.

Star Category	Hotels	% Charging Resort Fees	Avg. Price at Hotels With No Resort Fee	Avg. Price at Resort Fee Hotels	Avg. Resort Fee
1.0	46	8.7%	$69.98	$77.25	-
1.5	1,143	3.3%	$63.51	$64.76	$3.57
2.0	14,236	3.5%	$76.89	$86.49	$5.68
2.5	12,078	3.9%	$105.28	$121.01	$8.50
3.0	8,107	9.2%	$128.58	$144.13	$15.18
3.5	3,003	14.8%	$152.47	$177.85	$18.14
4.0	1,533	28.0%	$201.07	$201.24	$23.04
4.5	239	36.8%	$272.05	$291.77	$29.49
5.0	201	28.9%	$420.72	$318.86	$30.43
Total	40,586	**6.8%**	**$105.90**	**$153.50**	**$16.73**

Table A8: Robustness Checks for Different Definitions of Competition

	Binary Dependent Variable: Resort Fees Charged?					
	hotel_comps = Hotels In Half-Mile Radius		*hotel_comps* = Hotels In One-Mile Radius		*hotel_comps* = Hotels In Five-Mile Radius	
	(1)	(2)	(3)	(4)	(5)	(6)
hotel_comps	0.011***	0.006	0.007***	0.006*	0.002***	0.006***
	(0.004)	(0.004)	(0.002)	(0.003)	(0.001)	(0.002)
vrs	0.004***	0.002***	0.004***	0.002***	0.004***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
stars	−0.008**	−0.007*	−0.008**	−0.007*	−0.008**	−0.007*
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
rooms	0.000	0.000**	0.000	0.000**	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
chain	−0.049***	−0.052***	−0.049***	−0.052***	−0.049***	−0.052***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
roomshare	−0.009	−0.010	−0.009	−0.010	−0.009	−0.010
	(0.009)	(0.017)	(0.009)	(0.017)	(0.009)	(0.017)
any_comps	0.007	0.006	0.007	0.006	0.007	0.006
	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)
pc_comps_chain	−0.017***	−0.016*	−0.017***	−0.016*	−0.017***	−0.016*
	(0.005)	(0.009)	(0.005)	(0.009)	(0.005)	(0.009)
seasonality	0.029***		0.029***		0.029***	
	(0.009)		(0.009)		(0.009)	
pc_bus	−0.114***		−0.114***		−0.114***	
	(0.014)		(0.014)		(0.014)	
pc_english	−0.038		−0.038		−0.038	
	(0.038)		(0.038)		(0.038)	
Add'l Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Add'l Market Controls	Yes	Absorbed	Yes	Absorbed	Yes	Absorbed
Market Fixed Effects	MSA	ZIP-5	MSA	ZIP-5	MSA	ZIP-5
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,582	80,582	80,582	80,582	80,582	80,582
R-squared	0.28	0.40	0.28	0.40	0.28	0.40

Standard errors in parentheses reflect clustering at the ZIP-5 level
(8,864 clusters)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note that the number of hotel competitors (hotel_comps) is measured here in units of ten; the number of vacation rentals (vrs) is measured in hundreds.

Table A9: Resort Fee Magnitude Appears To Be Uncorrelated with Ratings

	Dependent Variable: Average (Cumulative) Hotel Rating		
	(1)	(2)	(3)
resort_fee_amount	-0.001		
	(0.002)		
resort_fee_pc_price		0.304	
		(0.199)	
log_resort_fee_amount			0.045
			(0.031)
stars	0.361∗∗∗	0.358∗∗∗	0.354∗∗∗
	(0.044)	(0.043)	(0.044)
log_price	0.378∗∗∗	0.413∗∗∗	0.370∗∗∗
	(0.047)	(0.048)	(0.045)
log_rooms	-0.107∗∗∗	-0.108∗∗∗	-0.109∗∗∗
	(0.026)	(0.026)	(0.026)
optional_fees	-0.056 ∗∗	-0.057 ∗∗	-0.056 ∗∗
	(0.026)	(0.026)	(0.026)
Chain Fixed Effects[a]	Yes	Yes	Yes
Detailed Firm Controls[a]	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes
Observations	1,218	1,218	1,218
R-squared	0.68	0.68	0.68

Standard errors in parentheses reflect clustering at the ZIP-5 level *(533 clusters)*

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] *See Tables A3 and A4 in the Appendix for details.*

Table A10: Summary Statistics by Review Source

	Reviews for "Included" Fee Hotels		**Reviews for "Separate" Fee Hotels**	
	Expedia/Hotels.com	TripAdvisor	Expedia/Hotels.com	TripAdvisor
Average Rating	3.84	4.09	3.89	4.12
Reviewers from U.S.	83.3%	84.9%	79.2%	82.5%
Trip Type:				
% Other/Unspecified	37.4%	8.77%	38.4%	9.6%
% Business *(of specified)*	14.9%	14.8%	15.4%	17.7%
% Couple *(of specified)*	34.8%	34.4%	35.3%	37.5%
% Family *(of specified)*	39.6%	40.2%	38.6%	31.9%
% Friends *(of specified)*	10.7%	10.6%	10.7%	12.9%

References

[1] Ahmetoglu, G., A. Furnham, and P. Fagan. 2014. Pricing practices: A critical review of their effects on consumer perceptions and behaviour. ***Journal of Retailing and Consumer Services***, 21(5): 696-707.

[2] Akerlof, G. and R. Shiller. 2015. ***Phishing for fools: the economics of manipulation and deception***. Princeton University Press.

[3] Anderson, C. 2012. The impact of social media on lodging performance. ***Cornell Hospitality Report***, 12(15): 6-11.

[4] Angulo, N. April 10, 2014. StubHub bets on 'all-in' pricing strategy, sees growth. ***Fox Business.***

[5] Ayres, I. and B. Nalebuff. 2003. In praise of honest pricing. ***MIT Sloan Management Review***, 45(1): 23-28.

[6] Bachman, J. September 11, 2014. Southwest hangs up its low cost jersey. ***Bloomberg.***

[7] Bagehot, W. 1873. ***Lombard Street: A Description of the Money Market.*** London: Henry S. King and Co.

[8] Becker, G. 1957 ***The economics of discrimination: an economic view of racial discrimination***. University of Chicago.

[9] Bender, A. September 9, 2014. Airline profits are up, thanks to everything but airfares. ***Forbes.***

[10] Bennett, V., L. Pierce, J. Snyder, and M. Toffel. 2013. Customer-driven misconduct: How competition corrupts business practices. ***Management Science***, 59(8): 1725-1742.

[11] Benston, L. August 12, 2010. Harrah's sees $$ in resort-fee anger. ***The Las Vegas Sun.***

[12] Bertini, M. and L. Wathieu. 2008. Attention arousal through price partitioning. ***Marketing Science***, 27(2): 236-246.

[13] Brown, J. and A. Goolsbee. 2002. Does the Internet make markets more competitive? Evidence from the life insurance industry. ***Journal of Political Economy***, 110(3): 481-507.

[14] Brown, J., T. Hossain, and J. Morgan. 2010. Shrouded attributes and information suppression: evidence from the field. ***The Quarterly Journal of Economics***, 125(2): 859-876.

[15] Cabral, L., and A. Hortacsu. 2010. The dynamics of seller reputation: evidence from eBay. ***The Journal of Industrial Economics***, 58.(1): 54-78.

[16] Ci, H.B., Q. Liu, and G. Xiao. 2005. Does competition encourage unethical behavior? The case of corporate profit hiding in China. ***The First Asia Corporate Governance Conference***. Shanghai, China.

[17] Carlin, B. 2009. Strategic price complexity in retail financial markets. ***Journal of Financial Economics***, 91(3): 278-287.

[18] Cheema, A. 2008. Surcharges and seller reputation. ***Journal of Consumer Research***, 35(1): 167-177.

[19] Chetty, R., A. Looney, and K Kroft. 2009. Salience and taxation: theory and evidence. ***The American Economic Review***, 99(4): 1145-1177.

[20] Chiles, B. 2017. Resorting to obfuscation: why do firms adopt shrouded pricing? *Working Paper.*

[21] Chiles, B. 2017. Shrouded prices and firm reputation: evidence from the U.S. hotel industry. Available at SSRN 2952950.

[22] Chioveanu, I., and J. Zhou. 2013. Price competition with consumer confusion. ***Management Science***, 59(11): 2450-2469.

[23] Dahremoller, C. 2013. Unshrouding for competitive advantage. ***Journal of Economics & Management Strategy***, 22(3): 551-568.

[24] Dastin, J. June 30, 2015. JetBlue Airways adds $20 checked bag fee per one-way trip. ***Reuters.***

[25] Dellarocas, C. 2003. The digitization of word of mouth: promise and challenges of online feedback mechanisms. ***Management Science***, 49(10): 1407-1424.

[26] Elliott, C. July 9, 2015. Is the FTC doing enough to stop those mysterious hotel 'resort fees'? ***The Washington Post.***

[27] Elliott, C. June 16, 2016. There may be an end in sight for controversial – and often invisible – resort fees. ***The Washington Post.***

[28] Ellison, G. 2005. A model of add-on pricing. ***Quarterly Journal of Economics***, 120(2):585-637.

[29] Ellison, G. 2006. Bounded rationality in industrial organization. ***Econometric Society Monographs***, 42: 142.

[30] Ellison, G., and S.F. Ellison. 2009. Search, obfuscation, and price elasticities on the internet. ***Econometrica***, 77(2): 427-452.

[31] Ellison, G., and A. Wolitzky. 2012. A search cost model of obfuscation. ***The RAND Journal of Economics***, 43(3): 417-441.

[32] Ellison, S.F. 2016. Price search and obfuscation: An overview of the theory and empirics. ***The Handbook on the Economics of Retailing and Distribution***: 287-305.

[33] Finnegan, A. June 11, 2010. Wynn Resorts tacks on mandatory $20 resort fee. ***The Las Vegas Sun.***

[34] Fisher, E. December 16, 2013. TM+ pairs primary, secondary tickets. ***Sports Business Daily.***

[35] Fombrun, C. and M. Shanley. 1990. What's in a name? Reputation building and corporate strategy. ***Academy of Management Journal***, 33(2): 233-258.

[36] Gabaix, X., and D. Laibson. 2006. Shrouded attributes, consumer myopia, and information suppression in competitive markets. ***Quarterly Journal of Economics***, 121(2): 505-540.

[37] Greenleaf, E., E. Johnson, V. Morwitz, and E. Shalev. 2015. The Price does not Include Additional Taxes, Fees, and Surcharges: A Review of Research on Partitioned Pricing. ***Journal of Consumer Psychology.***

[38] Grobart, S. January 25, 2012. TiqIQ: The Kayak of live-event tickets. ***The New York Times.***

[39] Grossman, S. 1981. The informational role of warranties and private disclosure about product quality. ***The Journal of Law and Economics***, 24(3): 461-483.

[40] Grubb, M. 2015. Failing to choose the best price: Theory, evidence, and policy. ***Review of Industrial Organization***, 47(3): 303-340.

[41] Gu, Y. and T. Wenzel. 2014. Strategic obfuscation and consumer protection policy. ***Journal of Industrial Economics***, 62(4): 632-660.

[42] Handel, B. 2013. Adverse selection and inertia in health insurance markets: When nudging hurts. ***The American Economic Review***. 103(7): 2643-2682.

[43] Heo, C. and S. Lee. 2011. Influences of consumer characteristics on fairness perceptions of revenue management pricing in the hotel industry. ***International Journal of Hospitality Management***, 30: 243-251.

[44] Heyes, A. and S. Kapur. 2012. Angry customers, e-word-of-mouth and incentives for quality provision. ***Journal of Economic Behavior & Organization***, 84: 813-828.

[45] Hossain, T., and J. Morgan. 2006. Plus shipping and handling: revenue (non) equivalence in field experiments on eBay. ***Advances in Economic Analysis & Policy***, 5.2.

[46] Housel, M. April 10, 2015. Stop deluding yourself about investing expenses. ***The Wall Street Journal.***

[47] Jansen, B. October 26, 2016. Southwest weighs extra fees, just not on bags. ***USA Today.***

[48] Josang, A., R. Ismail, and C. Boyd. 2006. A survey of trust and reputation systems for online service provision ***Decision Support Systems***. 43: 618-644.

[49] Kalayci, K. 2015. Confusopoly: competition and obfuscation in markets. ***Experimental Economics***. 19(2): 299-316.

[50] Kalayci, K. and J. Potters. 2011. Buyer confusion and market prices. ***International Journal of Industrial Organization***. 29: 14-22.

[51] Kahneman, D., J. Knetsch, and R. Thaler. 1986. Fairness as a constraint on profit seeking: Entitlements in the market. ***The American Economic Review***: 728-741.

[52] Karp, H. March 26, 2014. StubHub sings the blues after shifting fees. ***The Wall Street Journal.***

[53] Klein, B. and K. Leffler 1981. The role of market forces in assuring contractual performance. ***Journal of Political Economy***. 89(4): 615-641.

[54] Lal, R. and D. Kiron. June 15, 2005. CarMax. ***Harvard Business School***, Case 9-505-080.

[55] Lee, Y., and C. Han. 2002. Partitioned pricing in advertising: Effects on brand and retailer attitudes. ***Marketing Letters***, 13(1): 27-40.

[56] Luca, M. Reviews, reputation, and revenue: The case of Yelp. com. (September 16, 2011). Harvard Business School NOM Unit Working Paper 12-016 (2011).

[57] Luca, M. and G. Zervas. 2016. Fake it till you make it: Reputation, competition, and Yelp review fraud. ***Management Science***. 62(12): 3412-3427.

[58] MacLeod, B. 2007. Reputations, relationships, and contract enforcement. ***Journal of Economic Literature***, 45(3): 595-628.

[59] Matute-Vallejo, J., R. Bravo, and J. Pina. 2011. The influence of corporate social responsibility and price fairness on customer behavior: Evidence from the financial sector. ***Corporate Social Responsibility and Environmental Management***, 18(6): 317-331.

[60] Maynard, M. June 13, 2008. Two more airlines to charge for first bag. ***The New York Times.***

[61] Mayzlin, D., Y. Dover, and J. Chevalier. 2014. Promotional reviews: An empirical investigation of online review manipulation. ***The American Economic Review***, 104.8: 2421-2455.

[62] McCartney, S. January 27, 2016. How booking sites influence which hotels you pick. ***The Wall Street Journal.***

[63] McDowell, E. June 7, 2000. With special e-fares, online bookings soar. ***The New York Times.***

[64] McWilliams, A. and D. Siegel. 2001. Corporate social responsibility: A theory of the firm perspective . ***Academy of Management Review***, 26(1): 117-127.

[65] Milgrom, P. 1981. Good news and bad news: Representation theorems and applications. ***The Bell Journal of Economics***: 380-391.

[66] Miravete, E. 2013. Competition and the use of foggy pricing. ***American Economic Journal: Microeconomics***, 5(1): 194-216.

[67] Mogelonsky, L. December 12, 2012. Overcoming the loyalty erosion problems of drip pricing. ***Hotel Business Review.*** Available at http://hotelexecutive.com/business_review/3233.

[68] Moore, T. June 29, 2015. Travel advocates target hotels' big hidden fees. ***The Washington Post.***

[69] Morwitz, V., E. Greenleaf, and E. Johnson. 1998. Divide and prosper: Consumers' reaction to partitioned prices. ***Journal of Marketing Research***, 35: 453-463.

[70] Muir, D., K. Seim, and M.A. Vitorino. 2013. Drip pricing when consumers have limited foresight: evidence from driving school fees. Available at SSRN 2220986.

[71] Ayres, I. and B. Nalebuff. 2003. In praise of honest pricing. ***MIT Sloan Management Review***, 45(1): 23-28.

[72] O'Connor, A. and M. Meister. 2008. Corporate social responsibility attribute rankings. ***Public Relations Review***, 34(1): 49-50.

[73] Ott, M., Y. Choi, C. Cardie, and J. Hancock. 2011. Finding deceptive opinion spam by any stretch of the imagination. ***Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics***, 309-319.

[74] Pawlowski, A. February 22, 2013. Caesars reverses, adds resort fee to Las Vegas hotels. ***NBC News.***

[75] Peoples, G. October 20, 2014. Ticketmaster vs. StubHub: who's winning the resale battle? ***Billboard.***

[76] Piccione, M. and R. Spiegler. 2012. Price competition under limited comparability. ***Quarterly Journal of Economics***, 127(1): 97-135.

[77] Resnick, P., Zeckhauser, R., Swanson, J., and Lockwood, K. 2006. The value of reputation on eBay: A controlled experiment. ***Experimental Economics***, 9(2), 79-101.

[78] Roberts, P. and G. Dowling. 2002. Corporate reputation and sustained superior financial performance. ***Strategic Management Journal***, 23(12): 1077-1093.

[79] Roman, S. 2010. Relational consequences of perceived deception in online shopping: the moderating roles of type of product, consumer's attitude toward the internet, and consumer's demographics. ***Journal of Business Ethics***, 95(3): 373-391.

[80] Sablich, J. March 27, 2017. Those pesky airline fees and how to avoid them. ***The New York Times.***

[81] Sachs, A. January 26, 2017. There goes tradition: Las Vegas Strip casinos start charging for parking. ***The Washington Post.***

[82] Sainz, A. March 6, 2007. Spirit charges for baggage, cuts fares. ***The Associated Press.***

[83] Sandoval, G. May 18, 2002. Southwest soars without travel sites. ***CNET.***

[84] Schwartz, D. 2013. Concentration on the Las Vegas Strip: An exploration of the impacts. ***Gaming Law Review and Economics***, 17(9): 619-634.

[85] Sharkey, J. August 12, 2013. Barrage of fees is starting to follow fliers to the hotel. ***The New York Times.***

[86] Shea, C. June 25, 2006. The hidden economy. ***The Boston Globe.***

[87] Shleifer, A. 2004. Does competition destroy ethical behavior? ***AER Papers and Proceedings***: 414-418.

[88] Silk, R. January 24, 2017. DOT's proposed baggage-fee rule might not survive Trump. ***Travel Weekly.***

[89] Smith, E. August 31, 2015. StubHub gets out of 'all-in' pricing; after losing business, ticket reseller reverts to tacking on fees at checkout. ***The Wall Street Journal.***

[90] Smith, M., and E. Brynjolfsson. 2001. Consumer decision-making at an Internet shopbot: brand still matters. ***Journal of Industrial Economics***, 49(4): 541-558.

[91] Snyder, J. 2010. Gaming the liver transplant market. ***The Journal of Law, Economics, & Organization***, 26(3): 546-568.

[92] Spiegler, R. 2006. Competition over agents with boundedly rational expectations. ***Theoretical Economics***, 1(2): 207-231.

[93] Standifird, S. 2001. Reputation and e-commerce: eBay auctions and the asymmetrical imact of positive and negative ratings. ***Journal of Management***, 27: 279-295.

[94] Sylvester, R. February 21, 2013. Caesars to start charging resort fees, says guests demanding them. ***Las Vegas Sun.***

[95] Team, T. April 8, 2014 Competitive landscape of the U.S. online travel market is transforming. ***Forbes.***

[96] Team, T. September 30, 2015 An update on the online travel agencies. ***Forbes.***

[97] Tesler, L.G. 1980. A theory of self-enforcing agreements. ***Journal of Business***, 53(1): 27-44.

[98] Tuttle, B. March 26, 2013. Southwest Airlines: We're not really about cheap flights anymore. ***Time.***

[99] Tversky, A. and D. Kahneman. 1975. Judgment under uncertainty: Heuristics and biases. ***Utility, probability, and human decision making***. Springer Netherlands: 141-162.

[100] Wenzel, T. 2014. Consumer myopia, competition and the incentives to unshroud add-on information. ***Journal of Economic Behavior & Organization***, 98: 89-96.

[101] White, M. July 6, 2015. Free hotel Wi-Fi is increasingly on travelers' must-have list. ***The New York Times.***

[102] Wilson, C. 2010. Ordered search and equilibrium obfuscation. ***Journal of Industrial Organization***, 28(5): 496-506.

[103] Winship, T. March 20, 2013. Southwest: Not the low-fare leader you thought. ***Smarter Travel.***

[104] Xia, L., and K. Monroe. 2004. Price partitioning on the internet. ***Journal of Interactive Marketing***, 18.4: 63-73.

[105] Xia, L., K. Monroe, and J. Cox. 2004. The price is unfair! A conceptual framework of price fairness perceptions. ***Journal of Marketing***, 68.4: 1-15.

[106] Zervas, G., D. Proserpio, and J. Byers. 2014. The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. ***Journal of Marketing Research***.

[107] Zhang, B. January 18, 2017. American Airlines is banning carry-on bags and overhead bin use for basic-economy passengers. ***Business Insider.***