Online Reputation Mechanisms and the Decreasing Value of Chain Affliation

Hollenbeck, Brett

UCLA Anderson School of Management

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Brett Hollenbeck*

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Abstract

This paper investigates the value of branding and how it is changing in response to a large increase in consumer information provided by online reputation mechanisms. As an application of umbrella branding, theory suggests much of the value to firms of chain affiliation results from asymmetric information between buyers and sellers. As more information becomes available, consumers should rely less on brand names as quality signals and the ability for firms to extend reputations across heterogenous outlets should decrease. To examine this empirically, this paper combines a large, 15 year panel of hotel revenues with millions of online reviews from multiple platforms and performs a machine learning analysis of review text to recover latent, time-varying dimensions of firm quality. I find that branded, or chain-affiliated, hotels earn substantially higher revenues than equivalent independent hotels, but that this premium has declined by over 50% from 2000 to 2015. I find that this can be largely attributed to an increase in online reputation mechanisms, and that this affect is largest for low quality and small market firms. Numerous measures of the information content of online reviews show that as information has increased, independent hotel revenue grows substantially more than chain hotel revenue. Finally, the correlation between firm revenue and brand-wide reputation is decreasing and the correlation with individual hotel reputation is replacing it.

*UCLA Anderson School of Management, contact brett.hollenbeck@anderson.ucla.edu. I wish to thank the Morisson Family Center for Marketing Research for generous funding.

The past decade has seen a dramatic change in both the nature of and amount of information available to consumers. Beginning in the mid-2000's, online reputation mechanisms like TripAdvisor, Yelp, and the reputation and reviews portions of Amazon, eBay, Alibaba and other retailers, have produced an influx of detailed information on the quality and attributes of goods and services. These new sources of information have potentially large implications for how consumers make choices. One implication is that consumers may rely less on traditional signals of quality like price, branding, and advertising.[1]

This study examines the implications of this information for business-format franchising as an application of umbrella branding more broadly. Branding exists in large part to provide a reliable signal of product quality.[2] In settings where there is asymmetric information between buyer and seller, branding allows sellers to establish reputations over many interactions. Firms may use umbrella branding to extend the reputations developed over past products to new products and services.

The formation of chains using business format franchising has become widely used in retail and service industries, generating sales responsible for over 3% of GDP in 2007 (Kosova and Lafontaine (2012).) Under this model, a local entrepreneur typically owns and operates a business while licensing its branding and, in most circumstances, agreeing to purchase inputs and follow standard operating procedures. In return, the franchisee pays the franchisor a fixed fee and a share of revenue. Much of the benefit to the franchisee comes via licensing the brand name that, as described in Aaker (1995), provides four benefits: awareness, perceived quality, specific mental associations, and loyalty. The first two of these rely on asymmetric information. In other words, firms use umbrella branding to extend the reputations developed over past products to new products and services.[3]

A chain firm's reputation for quality is costly and time-consuming to build and a major source of its value. Firms across industries invest large amounts of resources in developing their brand and reputation. While the franchise literature implicitly recognizes the importance of quality reputation effects within chains, no previous work has fully explored the implications for franchising of improving consumer information, or the effects of online ratings on the value of franchising more generally.[4]

This paper empirically examines three research questions. How have online reputation mechanisms affected the value of chain affiliation and business-format franchising? How is the relationship between online reputation mechanisms and brand value determined by vertical differentiation and market size? Finally, is chain reputation decreasing in importance and, if so, what are the implications of this for franchise contracts? I document that, as more information has become available, the value of chain affiliation has declined significantly. In addition there is substantial heterogeneity in the size of the effect determined by vertical differentiation and market size. Finally, brand-level reputation is declining as a predictor of firm

[1]The potential impacts of have been hypothesized at length in Simonson and Rosen (2014) and in the popular press (Surowiecki (2014).)

[2]Early theoretical work on brands emphasized the importance of and challenge of forming a reputation for quality (Shapiro (1983)) and brands as a signal of quality (Milgrom and Roberts (1986), Spence (1974), Park et al. (1986)).

[3]The conditions under which brand extension can signal product quality have been explored theoretically (Moorthy (2012)) and shown empirically (Erdem (1998).)

[4]For an overview of the role of quality reputation in chain firms, see Blair and Lafontaine (2005).

performance and outlet-level quality is increasing as a predictor.

Much previous work on online reviews, including Chevalier and Mayzlin (2006), Chintagunta et al. (2010), and Zhang and Zhu (2010), attempt to identify a causal effect of average online rating on outcomes like sales. Unlike this work, I do not study the effect of star rating on sales. In that context, average star rating's close relationship with underlying quality makes it difficult to identify a separate causal effect. Instead, I take advantage of this relationship and treat the star ratings and content of reviews as useful measures of product quality. I go beyond star rating to measure quality along many separate dimensions as revealed by text analysis. The focus here is on the implications of increased product information on the gap in performance between chain and independent firms. I use a very large and detailed panel to construct comprehensive measures of amount of information available through online reputation mechanisms and time-varying quality as revealed through online ratings.

The setting is the hotel industry, which is an ideal industry for considering these issues. It is a large and important sector which is largely franchised and whose product is an experience good. Historically, consumer information about specific hotel properties has been relatively low, often limited to the name, location and price, and perhaps a few lines in a guidebook. A hotel's brand name has been one of the most salient and important signals of its underlying quality. By contrast, beginning in the mid-2000's and growing rapidly since then, a number of widely used online platforms now offer highly detailed user-generated reviews and quality ratings.[5] The hotel industry offers other advantages as well; competition is primarily geographic and firms offer a single basic product, a night's stay in a room, that is differentiated primarily vertically and according to quality tiers widely agreed upon within the industry. In addition, this setting features many independent firms that offer a useful counterfactual against which to measure the value of umbrella branding via franchising.

This study combines a large, 15 year, property-level panel of hotel revenues with roughly 1.5 million online reviews from multiple platforms. The empirical strategy is to take advantage of the changing level of online information available to consumers over time, markets, and firms to measure the aggregate performance of chain firms vs independent firms and explore differential effects of information on performance across different types of firms and brands. In particular, I leverage the large and highly granular data on both revenue and reviews as well as the fact that many firms add, drop or switch chain affiliations in the sample period. I also use instrumental variables constructed from two exogenous changes in TripAdvisor.com's review policies. These changes generate exogenous variation in the amount of information posted on TripAdvisor.com both in number of reviews and characters, and when included as instruments confirm the main results.

The rich text data associated with the reviews is an additional strength. I use Latent Dirichlet Allocation, an unsupervised machine learning algorithm, to model the high-dimensional text data into distinct topics and then calculate a separate ratings valence along each topic. This serves two purposes. First, it strengthens the empirical analysis by controlling for time-varying hotel quality along each dimension separately. Second,

[5] According to the Local Consumer Review Survey 2012, 85% of consumers checked online reviews before making purchasing decisions in 2012.

it provides results on which quality dimensions are most associated with increases or decreases in revenue.

I find the following three main results. First, the amount of information consumers have on a specific outlet, measured in four separate ways, has a significant positive effect on revenues of independent hotels but no effect on chain hotels. Receiving more reviews, longer reviews, more unique terms, and more recent reviews all increase independent hotel revenues but have no association with revenue for chain hotels. This effect size is not uniform across the vertical quality dimension. It is mostly driven by low quality independent firms, which benefit the most from higher numbers of reviews. These firms are also the most negatively affected by negative ratings and high variance in ratings.

In order to quantify the cumulative effect of reviews I next measure the aggregate change in the revenue gap between chain and independent firms from 2000-2015. There exists a large advantage associated with chain affiliation, the result of which is a revenue premium of 25.1% over otherwise identical independent firms. This premium remains large but has fallen substantially over the years 2000-2015, from 31.8% to 19.3%. Again, the decline is not uniform and relates both to vertical differentiation and market size. It has fallen particularly far for low quality firms and firms in small or rural markets. Third, within chain hotels I find a shift in the relative importance of brand reputation versus individual product quality. The average correlation between revenue and brand-level reputation is decreasing over time and the correlation with property-level ratings is increasing over time.

Altogether these results suggest online reputation mechanisms have had a large impact on the value of franchising and chain affiliation, and that consumers value the quality signal branding provides particularly for low-quality and small market firms where the risk of an adverse experience is relatively high. These results also point to an increase in the relative importance of individual product quality and characteristics and a decrease in the relative importance of brand reputation. This has implications for the franchising model and umbrella branding more broadly. The overall value of joining a chain and in effect renting its brand name is falling, particularly at the low end of the quality scale. In addition, franchisee-franchisor relationships are based on royalty contracts designed to incentivize chain members to provide high quality. This incentive is becoming less important as spillovers across chain members diminish.

This paper is the first to consider the implications of online reputation mechanisms on umbrella branding and franchising and the first to show directly that online reviews are decreasing the value of chain affiliation. This contributes to the literatures on franchising by first empirically quantifying the value of chain affiliation and then using online reviews to show how much of this value relates to quality signaling and how this varies over types of brands. This paper also contributes to the literature on online word-of-mouth (WOM) by focusing on the implications of the information content of online reviews.

The rest of this paper is organized as follows. In section 1 I review the related literature and contribution. In section 2 I describe the data collected and industry setting. In section 3 I show results on the impact of online reviews on different firm types. In section 4 results are presented quantifying the revenue premium earned by chain firms and showing this premium is declining over time. Section 5 presents results on the changing correlation between brand reputation and property level ratings with revenue. Section 6 concludes.

1 Literature Review

This paper relates to several literatures. The first is the study of franchising. Kosova and Lafontaine (2012) and Lafontaine and Shaw (2005) survey a variety of empirical work on business format franchising and franchised chains. A great deal of work has been done in the vertical integration and franchising literature on why and when chain firms own and manage their own outlets and when they franchise them out. This literature implicitly recognizes the importance of quality reputation effects as a primary source of value for chains but none explicitly measure it or study how online reputation sites may be changing it. Several notable works study issues related to franchising in the hotel industry. These include, Kosova et al. (2013) who study the relationship between organizational form and performance within a major chain, Kim and Jap (2016) who studies franchise encroachment, Kalnins (2016) which studies the use of pricing as quality signaling within hotel chains, and Tsai et al. (2015) who study the effects of rebranding.

This paper also contributes to the literature on branding, brand extension and the sources of brand value. This literature includes early theoretical work by Shapiro (1983), Milgrom and Roberts (1986), and Spence (1974) on the use of branding for reputation building and as a signal for quality. Sappington and Wernerfelt (1985) and Cabral (2000) show when and how firm reputations or brand associations transfer to new products. Park et al. (1986) present a framework under which brands develop reputations through product development and marketing communication. The brand then acts as a signal or heuristic cue to infer both quality and specific attributes (Maheswaran et al. (1992).)

In recent theoretical work, Miklos-Thal (2012) considers firm incentives to link products through umbrella branding, and finds that this can arise endogenously without differences in firm skill level or key inputs, and that rational consumers come to expect a consistent quality level across products under the same brand. Moorthy (2012) further develops our understanding of the conditions under which brand extension can signal product quality.

There is empirical support for the claim that consumers expectations of quality carry over within brands across different products. Erdem (1998) shows high correlation between consumers' quality perceptions of umbrella chain products. Further evidence is compiled in a secondary analysis in Bottomley and Holden (2001). Some notable recent empirical works on brand values and umbrella branding include Ailawadi et al. (2003) on using a revenue premium to measure brand equity and Goldfarb et al. (2009) on measuring brand value in an equilibrium framework. Notably, Waldfogel and Chen (2006) finds that the presence of online information reduces brand preferences, showing that shoppers who use price comparison sites are less likely to purchase from chain retailers.

This paper also contributes to the literature on online word-of-mouth (WOM) and user generated content (UGC.) A number of papers, including Chevalier and Mayzlin (2006), have studied the impact of online reviews on product sales. Chintagunta et al. (2010), and Zhang and Zhu (2010) also study the relationship between online reviews and sales. You et al. (2015) and Floyd et al. (2014) survey additional research on this subject. A closely related work is Luca (2011), who uses a regression discontinuity design to study the marginal effect of Yelp.com star ratings on Seattle restaurants. He finds a significant positive relationship between average star rating and restaurant revenues, and notably finds this relationship is larger for unchain restaurants than for chain restaurants.

Recently, Tirunillai and Tellis (2014) and Buschken and Allenby (2015) have suggested methods for analyzing and summarizing review text. Several recent papers study UGC and WOM specifically in the context of the hotel industry. These include Chevalier et al. (2016) and Proserpio and Zervas (2016) who study the impact of managerial replies on online ratings. Mayzlin et al. (2014) studies review manipulation and finds that hotels with a high incentive to fake reviews have higher ratings and their neighbors have more low ratings. Ghose et al. (2012) uses UGC from hotel reviews and other sources to study optimal ranking of search results.

2 Data and Setting

This section describes the data and industry setting. The unit of analysis throughout this paper is at the level of the individual property. Similarly, I define "firm" throughout at the level of the property because the vast majority of hotels are owned and managed by independent franchisees in these data.[6] Because the state of Texas collects a hotel occupancy tax, the full monthly revenues of all Texas lodging establishments is available from the Texas Comptroller of Public Accounts. This paper combines 15 years of monthly revenue data on 5,265 properties with a panel dataset containing the full history of online reviews for those same properties. Tax revenue data is particularly trustworthy because incorrectly reporting it is considered unlawful tax evasion. For each hotel I also collect location, capacity and age. This information, along with chain affiliation, was cross checked with a number of sources including the AAA Tourbook published each year and various hotels booking websites. The AAA Tourbook also provides a standardized measure of quality, giving a rating of 1 through 5 stars for each hotel listed based on a uniform criteria. These star ratings and the associated criteria are widely accepted in the industry as denoting distinct quality tiers. The remainder of this paper will use both subjective online ratings and objective AAA ratings as measures of quality, but will refer to a property's AAA star rating as its quality level.

The panel covers the years 2000-2015 and contains 5,265 total firms in 548 cities. While the data is limited to one state, Texas is helpfully a very large and heterogenous state. It contains roughly 10% of the U.S. population and produces roughly 10% of U.S. GDP, making it the 12th largest economy in the world, larger than Mexico or South Korea for instance. It contains a variety of distinct market types as well, ranging

[6] The organizational structure of chain affiliated hotels can vary. In some cases, the chain both owns and operates the property, in other cases a franchisee owns the property but the chain has a contract to manage it. While I do observe these contracts, in nearly all firms in this sample, the chain neither owns nor operates the property. Instead, these roles are taken by local franchisees and the chain simply licenses its branding and provides the franchisee with a operating manual.

from coastal resort areas, suburban markets, rural areas, and major urban centers, including 6 of the 20 largest cities in the U.S. For what follows, I delineate three market types, small, mid-sized and large. Small or rural markets have populations below 150,000 and are geographically isolated by being greater than 20 miles from a major population center. Mid-sized or suburban markets are defined as being geographically isolated medium-sized cities such as Lubbock as well as small cities within 20 miles of major cities. Large or urban markets are defined as the central areas of major cities.[7] In 2015, 37% of firms are in small markets, 27% are in mid-sized markets, and 35% are in large markets.

The tax return data provides total revenue but not prices or bookings. To measure performance, I instead use daily revenue per available room, or "RevPar". This is the industry standard measure of performance, and is computed simply as revenue divided by capacity and the number of days in the reporting period. Summary statistics can be seen in Table 1. All revenue data are adjusted for inflation using 2006 as the base year. Average RevPar for the full sample is \$39.7 and is substantially higher for chain firms and firms with higher AAA star ratings. One star firms average \$23.9 per room per day while five star hotels average \$345.6. In total, I observe \$89.4 billion in revenues during the sample period. The industry is growing rapidly in Texas during this time, with over 2,100 new entrants compared to 408 exits. The largest segment by far is the 3 star segment, followed by 2 stars and 1 star.

Overall, 62% of hotels in the data are members of regional or national chains. For the remainder of this paper, for simplicity I will refer to these hotels as chain and non-chain members as unchain or independent. Table 2 presents summary information on the 25 largest chains in Texas. The largest is Best Western with 275 unique properties. In the hotel industry, it is important to distinguish between parent companies and underlying brands. For instance, Hilton Worldwide offers 8 distinct brands in its portfolio, and the vast majority of brands are in similar portfolios with only a few exceptions. For the most part, I focus on the underlying brands in the empirical analysis, treating Hampton Inn and Hilton Garden Inn as separate, for example, despite both being members of Hilton Worldwide. In total, there are 70 distinct brands operating in Texas as defined at the individual brand level.

To supplement the panel of revenues, I collect ratings and reviews data from two major U.S. online travel platforms, TripAdvisor.com and Priceline.com. TripAdvisor was founded in 2000 as a travel search engine and aggregator. After several years, user reviews were added as a feature and quickly became the main driver of traffic. As of 2012 the site was receiving 65 million unique visitors per month. As Figure 1 shows, the share of firms listed has grown steadily since 2002, surpassing 50% in 2009. Priceline was founded in the late 1990's as an online travel agent, and began incorporating user generated reviews on hotel listings in 2005. TripAdvisor uses a 5 point quality scale whereas Priceline uses a 10 point scale.[8]

The data was collected by scraping all reviews off each site in March of 2015. This was down by crawling each site for all listed hotels in the state of Texas collecting the name, location information, and full text,

[7]There are 7 large markets in the data: Austin, Arlington, Dallas, El Paso, Fort Worth, Houston, and San Antonio.

[8]In what follows, they are mostly kept separate but when it is necessary to combine ratings onto a common scale the Priceline rating is simply divided in half to match the TripAdvisor scale.

rating and date of each review. To ensure completeness, a secondary search was performed for any hotel listed in tax data but not present in the initial scraping. When a hotel closes, its records are still stored by TripAdvisor and Priceline, so the data include hotels that exited during the sample period. Of 408 exiting firms, 104 have TripAdvisor reviews and 78 have Priceline reviews. This includes firms exiting as early as 2005.

In total, I collect 1.44 million full-text reviews posted between 2002 and 2015. Table 3 presents summary information on TripAdvisor.com reviews by firm type. As of 2015, 77.4% of Texas hotels are listed on TripAdvisor. Listed firms have an average of 130.7 reviews listed in 2015. The average number of reviews has grown nearly exponentially since online travel sites started displaying them in the early to mid-2000's, as Figure 2 shows. Summary statistics on all variables used in the paper are presented in Table 5.

2.1 Text Analysis

The data contain the full text of all reviews, a rich source of information that I take advantage of in three ways. First, I categorize each review term into topics based on an unsupervised learning algorithm and score each review on each topic. This allows the content of reviews, despite being very high-dimensional, to be incorporated into the empirical analysis in a simple and intuitive way. Second, after presenting results on the difference between chain and independent firms in their relationship between reviews and revenue I classify review terms based on firm type to study why reviews seem to have different effects. Third, I combine the topics-based analysis with the detailed revenue data to see which topics are most highly correlated with changes in revenue in the short term.

Text of user generated content has been analyzed using topic modeling previously by Tirunillai and Tellis (2014) and Buschken and Allenby (2015) who I follow in several respects. While text is rich and informative it is also extremely high-dimensional with a long right tail. Factor-analytic methods for dimension reduction have been found to have poor convergence and stability properties in this context. Instead, I implement the unsupervised machine learning algorithm Latent Dirichlet allocation (LDA) to reduce the text from a very high-dimensional space to a small number of topics. Rather than follow a rule-based analysis of the text of reviews, this method finds the groups of words and expressions which it designates as "topics" which tend to appear together in reviews. The topics capture the latent dimensions of each review which can be combined with that review's valence as expressed by the associated star rating so that both content and valence can be jointly represented in a reasonable number of dimensions.

First, the text is prepared by stripping out extremely common terms such as "the", "is", and "it" as well as punctuation marks and stopwords. Next, words are grouped together which share stems, such as "stay" and "stayed." Each review is then treated as a separate document and the relative co-occurrence of terms and expressions is used as the input to determine the topics. The model is unsupervised but we must determine the number of topics based on overall fit and subjective judgment of the outcomes.

The output of the LDA procedure is a probabilistic model representing how closely each word is associated with each topic as well as what mixture of topics is present in each review. The LDA was estimated for 2 through 15 topics and the output evaluated for each. Ultimately, 6 topics fit best and the results are shown in Table 4. Realistically, most reviews contain several topics and adding more topics to the model produced unstable results and topics with large amounts of overlap. For 6 dimensions the topics were associated with clearly interpretable concepts with relatively little overlap.

Table 4 shows the words most closely associated with each topic and the labels are given by subjective interpretation. Interpretation of this step is naturally subjective, but the topics seem to represent (1) description of the interior features of the hotel room such as "bathroom", "clean" or "towel", (2) terms associated with service issues and staff interactions such as "desk", "problem", and "told"/"said"/"asked", (3) references to specific brands or business related features such as "Marriott", "member" or "conference", (4) general descriptions of quality such as "great", "friendly", or "comfortable", (5) descriptions of location or external features such as "pool", "parking", or "walk", as well as a topic consisting of Spanish words and phrases. While this last topic is a useful confirmation that the topic modeling found distinct phrase groupings, reviews that were entirely written in Spanish or other languages are largely excluded from the analysis which follows. Reviews which contain both English and Spanish are still included.[9]

The bottom row of Table 4 shows the relative frequency of topics in the full set of reviews. Descriptions of the room are the most common topics, followed closely by service issues and general quality. Spanish terms and discussion of specific brands are much less frequent. Each review is then scored based on how closely it fits with each topic and these are compiled at the hotel and hotel-month level.

I make use of text data in two additional ways. First, by searching review text for use of the words "renovations," "construction," and variations on these terms. These do not represent a separate topic, but I use the results of this to construct two other variables, a dummy for whether a hotel is currently undergoing renovations and a dummy for whether is has undergone renovations in the past year. Second, in the next section I describe the use of Naive Bayes Classification to find what review terms are distinctly associated with chain versus independent status.

3 Measuring the Impact of Online Reputation Mechanisms

In this section I present the first main result, which measures the differential effect of online reputation mechanisms on revenue of chain and independent firms. Chain affiliation serves several functions, but a primary function is to license a brand name that signals quality to consumers who are unfamiliar with the good or service. The rapid expansion of online reputation mechanisms thus has potentially large implications for chain firms. The goal then is not to measure a causal effect of average rating but to measure the effect of quantity of information. To measure this, I construct four related measures of the amount of information

[9]TripAdvisor places these reviews in a separate part of the website. In parts of Texas a large share of the population speaks Spanish and many reviews contain mixes of Spanish and English, this last group is kept in the analysis and should be captured by inclusion of the "Spanish" topic.

available for each firm: number of reviews, number of total characters in posted reviews, total number of unique words posted, and presence of recent reviews. I then look to measure the effect of these variables interacted with firm type to test if online reputation sites have a differential effect on chain versus independent firms.

In this section, the key parameter of interest is the difference between the effects of quantity of information from online WOM on independent versus chain hotel outcomes. Measuring causal effects of online WOM variables can present an empirical challenge. The same underlying firm qualities that drive reviews also drive revenue. I take a four part strategy to eliminate these concerns. This strategy consists of property fixed effects, detailed measures of time-varying property quality, lagged dependent variables and lagged independent variables. The empirical strategy relies on the large size and granularity of the data to consider and control for the relevant confounds, most notably hotel characteristics, time-variation in quality, and serial correlation. This strategy would be incomplete if there are elements of time-varying quality reflected in the number of reviews but not captured by any of these measures constructed from the ratings corresponding to those reviews, and in particular these elements must effect revenue differentially for chain and independent firms. To the extent that this is possible, the results would be effected by those elements. As an additional check, I therefore also employ two sets of instrumental variables which confirm the main results.

3.1 Empirical Strategy

First, I include large numbers of fixed effects to control for the main sources of potential endogeneity. Specifically, I use property level fixed effects to control for unobserved time invariant hotel quality variables such as location, size, layout and major attributes. I also include owner/manager fixed effects, as many hotels change management during the sample period and many owners have multiple hotels. I include year and month fixed effects to control for time trends and seasonality and I interact these with market type to allow for different seasonal patterns or time trends in different markets.

While these control for trends and seasonality and time invariant hotel characteristics, hotel service quality may change over time. To account for this I include the average star rating on TripAdvisor and Priceline as a time-varying measure of quality. Several researchers in recent years have attempted to measure the causal impact of average online star rating on sales. This presents a significant empirical challenge as average star ratings are determined largely by underlying quality. In response, they have developed strategies for this problem that typically assume fixed product quality and some use quasi-random variation including in how ratings are presented to consumers (Luca (2011)), in cross-platform variation in ratings (Chevalier and Mayzlin (2006)), and in the sequential rollout across markets (Chintagunta et al. (2010)). Instead I treat the average rating as an unbiased measure of quality and the noise in ratings as standard measurement error. By using star ratings as a useful proxy for quality and not attempting to also measure a separate causal effect, I avoid this source of potential endogeneity.[10]

[10] Using average star ratings as a proxy for quality has been done by a number of previous studies, including Luca and Luca

In addition, once many reviews have been posted the average rating may be slow to adjust to short term changes in quality, and so I include as further controls the average rating of the most recent 5 reviews on TripAdvisor and Priceline as well as the average of all reviews posted in the past month as a moving average measure of quality. I also include the standard deviation of ratings from both sites. Next I directly incorporate the content of reviews using the results of the LDA topic model described in the previous section. First, by including the average share of reviews of each topic for each hotel. Second, I construct new variables to measure valence separately for each topic. To do this I categorize each review based on the topic it is most associated with. Then I calculate the share of reviews associated with each topic which are high (4 or 5 stars) as opposed to low (1 to 3 stars). Thus a hotel could potentially have a 1 on "room interior" if 100% of reviews about room interior were positive or a .25 on service if 25% of reviews about service quality were positive, as two examples. This provides a time-varying measure of quality across the main attributes described in the reviews. Finally, I also include the dummies for whether a hotel recently was renovated or is currently being renovated described above. Altogether, these variables should complement the property fixed effects by capturing time-varying elements of quality both overall and along each dimension of the semantic content.

I also include the average Revpar of each hotel's competitors in the same market as a measure of market level demand shocks. As a final control, I include a lagged dependent variable to capture any other time-varying unobservable revenue determinants and improve model fit. Given the presence of property fixed effects, probably the largest source of potential bias in the interaction term from time-variation comes from a hotel's decision whether to leave or join a chain in the sample period. I test this concern by separately estimating the following results with and without these firms and find no difference.

After eliminating all time-invariant factors and including a broad set of controls for both long-term and short-term changes in firm quality, there still may remain some potential correlation in the volume of reviews from short term demand shocks. These shocks could increase the number of reviews, characters or unique terms in a month as well as revenue. I eliminate this by using only the lagged value of each of these variables. This is also useful because many hotel stays are booked in advance. This eliminates concerns of a short term omitted variable correlated with both revenue and number of reviews. If this omitted variable was serially correlated, however, using lagged values may not be sufficient. Fortunately, this condition is testable. I follow the test for serial correlation in panel data suggested by Wooldridge (2002).[11] Conditional on the same covariates used in the specification shown in Table 8, the test shows no evidence of serial correlation in the remaining idiosyncratic term.

As robustness checks I then test estimation with two types of instrumental variables, both of the which confirm the results. The first uses exogenous policy changes on TripAdvisor.com to generate variation in informativeness of reviews. The second uses lags of number of reviews to rule out serial correlation in

(2017), Dellarocas et al. (2010), McDevitt (2014), Zervas et al. (2016), and De los Santos and Wildenbeest (2017). Glaeser et al. (2016) also cites the use of TripAdvisor reviews to measure firm quality as a promising prospect for future research.

[11] Drukker (2003) uses simulations to show this test performs well in medium sized samples.

demand or in omitted quality. For more discussion of this test and other tests used to rule out endogeneity see Appendix A.

3.2 Marginal Effects

To measure the effects of online information on different firm types, I construct four related measures of quantity of information available: total number of reviews posted, total number of characters in the stock of reviews, total number of unique words in the stock of reviews, and a dummy for whether or not a review has been posted in the most recent month. In each case the variable of interest is lagged one month to avoid simultaneity and the focus is on the interaction with firm type. For each of the four tests I estimate:

$$Log(RevPar_{imt}) = x_{imt}\beta_1 + \beta_2 c_{it} + \beta_3 \#reviews_{i,t-1} + \beta_4 c_{it} X \#reviews_{i,t-1} + time_t + owner_j + hotel_i + \epsilon_{imt}, \tag{1}$$

where i denotes hotel, m denotes market, and t denotes month. Firm characteristics are represented by x_{imt}, which includes the number and type of competitors in each market, age, capacity, average star rating on TripAdvisor and Priceline overall and in the short term, standard deviation of each set of ratings, the share of each topic in the review text, the share of each topic's reviews which are 4 or 5 stars, and the average RevPAR of the firms in the same market as a control for market level demand. Fixed effects for time, owner and the individual property are also included as well as interactions between month fixed effect and market. The main effect of number of reviews is captured by β_3, the effect of chain affiliation is captured by β_2, and the interaction between these is captured by β_4, the main object of interest in this section.

Table 6 shows the results from these tests. Column 1 shows the main result on the effect of number of reviews measured separately for chain and independent firms. The marginal effect of one additional review is positive for independent firms but not chain firms. Column 2 shows results for number of total characters posted about a hotel, after controlling for number of reviews posted. Conditional on number of reviews, the marginal effect of more characters is positive for independent hotels but not chain hotels.

Column 3 show results for number of unique words. If a new review contains only terms that have previously been posted in past reviews, it will not add to this measure. These types of reviews, which add little additional content, may not be very informative. In addition, most reviews sites allow consumers to search review text, and with more unique terms in the stock of reviews it will be more likely they will find the specific information they are interested in. The result is that, conditional on number of reviews, having more unique words posted has a significant positive effect for independent firms, although not for chain firms.

Fourth, I consider different effects of recent reviews versus old and "stale" reviews. This uses a dummy for whether or not at least one review has been posted in the most recent month. Recent reviews should be more informative than older reviews because they would contain information about any changes to quality or service that had occurred recently. The result is a positive effect of recent reviews for for independent hotels but not for chain hotels.

While these measures are correlated with one another, we nevertheless see a very consistent result across four different ways of measuring the information content available to consumers through online reputation mechanisms. In each case, this information has a larger positive effect for independent than chain hotels.

The text topic modeling provides several results as well. First, across all specifications a higher proportion of reviews being dedicated to service issues is associated with lower revenue, perhaps not surprisingly since service issues tend to be negative complaints. The proportion of reviews discussing business amenities and brand is significant and positive. The interaction between valence and topic shows that positive valence is associated with higher revenue for all topics, as we would expect since this measures valence. Notably most topic valences are not statistically significant separately from the overall valence. The two that that are significant are the room interior and service topics, which also have much higher magnitudes than the other topics. This suggests that scoring positively on room interior and customer service are most associated with higher future sales.

I next consider how these effects vary over brand quality and market size. Related to the theoretical literature on umbrella branding, we would expect information effects to be strongest for chains with lower quality brands or in settings where consumer risk aversion is high. Figures 4 and 5 show the effect is not uniform across quality levels or market types and in fact the difference is quite dramatic. Figure 4 shows the effect broken down by AAA stars. It shows that both the overall effect and the gap between chain and independent hotels is primarily driven by lower quality hotels, where more reviews have substantially increased the revenues of low quality independent firms in contrast to chain firms. Figure 5 shows that the effect is largest for both firm types in small markets but particularly for independent hotels in small markets. Both these results are consistent with expectations.

To further explore the difference in effects of reviews for different firm types, I perform an additional analysis of the review text. Specifically, I do a classification analysis using naive Bayes classification, similar to that in Netzer et al. (2016). This employs machine learning techniques to assign probabilistic classifiers to features of text based on predefined categories. For the category of chain versus independent, the method will identify which terms in the text are most predictive of whether a review refers to a chain or independent firm. This provides an intuitive notion of which terms are most unique to each firm type. A simple naive Bayes classification does not account for other variables such as quality level, so I condition on AAA star rating and run the algorithm in batches.

The results of this are shown in Table 7 which shows the 50 most distinctive words for each firm type along with a measure of how much more likely they are to appear alongside that type. Notably, for chain hotels 10 of the 14 most distinctive terms refer either to highways or airports. Independent hotels by contrast are much more likely to generate review terms such as "lodge", "historic", "quaint" and "charm" as well as the city name Fredericksburg, a town which has banned chain businesses. This is suggestive evidence of why the number of reviews is associated with larger changes in revenue for independent hotels. Specifically, the chain hotels are more likely to be chosen out of convenience and reviews are more likely to reflect that convenience rather than offering more informative content.

3.3 Instrumental Variable Robustness Check

While the results in the previous section are strongly suggestive, if the controls used to measure time-varying hotel quality are incomplete or imperfect there may be bias in the size of the effects. As a secondary test, I perform a robustness check using as instrumental variables two exogenous changes in TripAdvisor.com's review posting policies. For the first years of the website, there was no restriction on how long reviews could be. In June 2009, they implemented a 100 character minimum length for reviews. Then, in August 2012, they increased the minimum length to 200 characters. See Figure 6 for a visual representation of the effects of the policy change, which shows a sharp break in the number of characters in reviews posted.[12] The purpose of these policy changes was to increase the informativeness of each review by eliminating very short reviews which typically had little information content.

Eliminating these short and low-information reviews provides an exogenous shift with respect to the object of interest and notably this policy change had no impact on the average rating left by reviewers as shown in figure 7. These policy changes are unrelated to demand for hotel stays, but generate useful variation in both average number of reviews posted (by increasing the costs of posting a review) and number of characters posted per review.

Columns 2 and 3 show results from using the TripAdvisor review length policy change for number of reviews and number of characters, respectively. For both the first stage F-stat is above 10. The results are similar to the baseline results shown in column 1 but with a slightly higher magnitude, both for the number of reviews and the number of characters, which are the variables we would most expect to be affected by the policy changes. The higher magnitude might reflect that the policy effected not only number of reviews and characters, but also average informativeness. This is a useful robustness check but not a full substitute for the results in the paper which contain much more variation and can be used to measure effects across the quality spectrum as well as different market types.

4 Aggregate Implications for Brands

In this section I present the second main result. We have seen that online reputation mechanisms have a larger effect on independent firm revenue than chain firm revenue, but the marginal effect of a single review, character, or unique term is quite small. Given this, what can we expect to be the cumulative effect on the value of branding over time as consumers have accumulated a very large set of information on each firm? This section measures the aggregate effect on the value of branding over the years 2000-2015 and how this varies over firm and market type.

[12]Because the characters in the review title count towards the limit, some reviews have fewer than 200 characters in the body of the text.

To test this, I calculate the aggregate revenue premium earned by chain firms compared to equivalent independent firms and track its value over time. Specifically, the model for RevPar that I consider is:

$$Log(RevPar_{imt}) = x_{imt}\beta_1 + c_{it}\delta^c + market_m + time_t + owner_j + hotel_i + \epsilon_{imt}, \tag{2}$$

where x_{imt} denotes firm characteristics and includes the number and type of competitors in each market, age, capacity, average star rating on TripAdvisor and Priceline, standard deviation of each set of ratings, and the average RevPAR of the firms in the same market as a control for market level demand, c_{it} indicates whether a firm is a member of a chain in period t, and $market$, $time$, $owner_j$,and $hotel_i$ are fixed effects. The ultimate object of interest is δ^c, which is the remaining effect on revenue of chain affiliation after controlling for firm and market characteristics.

It is important to correct for potential correlation between chain affiliation and unobserved factors that impact revenue. For instance, if chain hotels were more likely to be built at better locations, this would cause upward bias in the estimate of the chain premium. Fortunately, 663 hotels add or drop chain affiliation in the sample period.[13] Because we observe these switches, I can include firm fixed effects and estimate δ^c off the subpopulation of switchers.[14] No firms that add or drop chain affiliation change their star rating, indicating that switches occur within well-defined quality tiers, rather than accompanying a significant change in underlying firm quality. Along with superficial changes in branding, joining a chain requires following a set of standardized operating procedures.[15] This identification strategy is the same as that of Tsai et al. (2015) and Hollenbeck (2017), who also study branding in the hotel industry.[16] A set of robustness checks on this strategy is presented in Appendix B.

Results from this estimation are in column 1 of Table 8. The FE regression suggests chain firms earn a quite substantial revenue premium compared with equivalent independent firms. The estimated chain premium is 25.2% of RevPar or roughly $\$170,000$ per year for an 80 room property.

This chain premium is the average over the 15 years in the sample. Of more interest is how the revenue premium varies from year to year, which can be measured by interacting the chain effect with year dummies. We are interested in seeing whether or not this premium is falling over time as online reputation mechanisms increase consumer information. The results can be seen in Figure 8 and Figure 9. The chain revenue premium, expressed as a percentage, steadily decreases over the decade, from 31.8% in 2000 to just under

[13]Roughly twice as many hotels add a chain affiliation as drop it.

[14]A similar strategy is used in Hollenbeck (2017)

[15]Each chain maintains an operating manual that is loaned to the franchisee upon opening or converting a new hotel. This document is confidential. Franchise agreements are typically not confidential and lay out a set of obligations for the franchisee to follow. Based on those that I have reviewed and the anecdotal responses of hoteliers I have spoken to, the franchisee must agree to the possibility of a pre-opening inspection and the franchisor maintains the right to conduct periodic inspections through the length of the agreement. These inspections might be random or might be prompted by guest satisfaction surveys, depending on the chain. If a property is found to be deficient in some way, they may be charged a fee by the franchisor or may be required to correct the deficiency.

[16]Tsai et al. (2015) studies the consequences of rebranding in the hotel industry, including decomposing the effect into brand effects and property-brand effects. Hollenbeck (2017) also examines chain affiliation incentives in the hotel industry, with a focus on a potential cost advantage associated with chain organization. The paper estimates firm costs in a structural dynamic model, part of the first stage of which is a reduced form revenue analysis.

19.3% in 2015.[17]

There is heterogeneity across both firm and market type in how the chain premium has fallen. As shown in Figure 8, the chain premium falls roughly 12 percentage points for 1 and 2 star firms, but with a much smaller trend for 3-5 star firms. This is noteworthy and consistent with the results in section 3. It suggests a bifurcation in the value of chain affiliation, where the value to low quality firms of affiliating is decreasing as the ability to signal a reliable quality level becomes less necessary. For high quality firms, the growth of loyalty programs or other factors may offset this effect. It is interesting to note that in percentage terms, the average chain premium during the whole sample is significantly lower for 2 star firms than for both 1 and 3 star firms. It may be that business travelers value brands for loyalty programs and reliability at the 3 star level and price-sensitive consumers value chains at the 1 star level out of risk aversion, but that for 2 star limited service hotels brands have little to offer.

For firms in small markets, the chain premium has fallen dramatically, from 25% to 6.9%. Similarly, in medium-sized towns and suburban markets it has fallen from 33.4% to 13.7%. By contrast, in denser urban areas, it has fallen only from 34.5% to 25.9%. Since urban markets are the largest and fastest growing markets, this has muted the overall pattern somewhat, but this result further suggests that firms about whom consumers are especially uninformed or risk averse have been most impacted by the change in information.

To investigate this further, Figures 10 and 11 show the raw trends in revenue for chain and independent firms, respectively. These revenues are adjusted for inflation and then normalized to their value in 2000. Chain firms appear more sensitive to the business cycle, perhaps due to a greater reliance on business travelers. Between 2000-2015, average inflation-adjusted chain revenue has declined for all quality categories except 3 star, which has stayed level. For 1 and 2 star firms, revenues decline 21% and 12%, respectively.

For independent firms, on the other hand, revenues have trended upwards over the period 2000-2015. The increase ranges from 8.4% for 3 star firms to 41.3% for 4 and 5 star firms. The combination of trends we see in Figures 10 and 11 suggest that the decline in the chain premium has been caused by both an increase in performance by independent hotels and a decrease by chain hotels, but with more of the effect resulting from an increase by independent firms.

5 Brand Reputation and Property Level Performance

This section presents the third main result. The previous results suggest online reputation mechanisms have a larger effect on independent hotels than chain hotels and that this cumulative impact of this has substantially reduced the revenue premium associated with chain affiliation. These results suggest that quality signaling is an important source of brand value. Within the subset of chain hotels, however, I test for an important

[17] This result does not appear to be caused by increasing numbers of chain competitors, as it is robust to different specifications that include the number of chain firms in each market, the share of chain firms, and the full type distribution in revenue estimates. In addition, while the US as a whole experienced a large recession in 2008-9, large regions in Texas were experiencing an economic boom at this time due to new gas production. Comparing this figure for counties with and without falling employment show no significant difference, suggesting business cycle dynamics do not play a major role in this result.

implication of this, which is a shift in the relative importance of brand reputation versus individual product quality. The premise of umbrella branding and franchising is that the reputation developed over existing products can be extended to signal quality of new products. As more outside information becomes available, however, the value of this signal should decrease. If this is true it has substantial implications for brand extension and product development. To test if this hypothesis is supported empirically, I restrict attention to chain firms and measure the relative importance of brand reputation and individual property quality for outcomes as well as how this changes over time.

To do so, I include the average TripAdvisor rating of all chain members as an independent variable alongside the average rating of the individual outlet. I treat average chain rating as a proxy for overall brand reputation. I continue to use average property-level rating as a measure of product quality and interact both of these measures with time. The full model is thus:

$$Log(RevPar_{imt}) = x_{imt}\beta_1 + \beta_{2,t}chainrating_{it} + \beta_{3,t}propertyrating_{i,t} + time_t + owner_j + hotel_i + \epsilon_{imt}, \quad (3)$$

where x_{imt} are the same covariates as before and noting the time subscript on the parameters $\beta_{2,t}$ and $\beta_{3,t}$. The top left plot in Figure 12 shows the results for the full sample of chain hotels. Notably, the coefficient on mean property-level rating is increasing over time and the correlation with chain-level rating is decreasing over time. Looking at all six plots, we see that the increase in correlation between outlet rating and revenue is fairly consistent across all firm and market types, rising from an initial level of roughly .05 at the beginning of the sample period to roughly .20 at the end. For the full sample, the coefficient on chain rating decreases from near .30 to roughly .20, but with wide heterogeneity across firm and market type. Comparing the different plots we see that the fall is most pronounced for low-quality chains, as measured by AAA ratings of 1 and 2 stars with little change for high quality brands. The decline in the correlation with brand reputation is also most pronounced in small and mid-sized markets. In large markets and for high-quality chains, the coefficient on chain ratings begins higher and shows little decline.

These results show a substantial decline in importance of brand reputation in determining individual property performance, and an increase in importance of individual property quality. The pattern in these results is consistent with the evidence in sections 2 and 3 regarding the heterogeneity of these effects across the vertical quality spectrum and across market size. For high quality chains, there has been little decline in the correlation between hotel performance and brand reputation. For small and rural markets, chain reputation is more important than individual property quality and, while this has fallen, it remains true at the end of the sample period. For mid-sized and urban markets, however, overall brand rating has decreased below property rating.

6 Conclusions

The previous sections have shown that the value of umbrella branding in the hotel industry has fallen significantly beginning in the mid-2000's and that this fall is at least partially due to information from online reputation mechanisms. This result is distinct from much prior research on online word-of-mouth that has sought to measure a causal effect of average online rating. Instead, I study the effect of amount of information available to consumers on the difference in performance between chain and independent firms. After constructing a large and detailed panel of online reviews and firm revenues, I can take advantage of the comprehensive nature of this data in several ways. First, it allows construction of a detailed and multifaceted set of variables measuring the amount of information available to consumers over time. Second, it allows for time-varying, multidimensional variables measuring quality at the firm level. These average ratings come from moving averages of ratings from multiple sites as well as the rich text data associated with them and serve as highly useful proxies for quality and how it varies over time.

The final product of this is three main results. First, the marginal effect of additional information on revenue is substantially higher for independent hotels than chain hotels. Indeed, after controlling for quality there is no positive association between the measures of consumer information and revenue for chain firms while there is a significant positive one for independent firms. Even if the controls used were imperfect, the difference in results across the two firm types is striking. This is particularly true when combined with the second main result, which is that the revenue premium earned by chain hotels has fallen by roughly half between 2000 and 2015. Third, the correlation between performance and brand reputation has fallen substantially while increasing for individual property quality. In addition, these effect are not uniform across chains, markets, or properties. This has implications for entrepreneurs considering making a large investment in a brand name via franchising fees, as the decline in brand value has mostly occurred among lower quality, limited service properties and those in rural and suburban markets. While it has fallen slightly, the value of chain affiliation for higher quality and urban firms remains high.

On a broader level, the declining value of branding as information becomes more readily available has potentially large implications for the franchisee-franchisor relationship. As Blair and Lafontaine (2005) describe, franchising contracts are premised on the negative externality involved in chains that is analogous to that in umbrella branding.[18] Each new chain partner has an incentive to free ride off the reputation of its partners and offer low quality, knowing that it will not bear the full cost of this. As a result, franchise contracts are composed of a fixed fee and a recurring share of revenue. Royalties typically range from $7-10\%$ of revenue, accounting for roughly half of the average revenue premium earned by chain-affiliated franchises in 2015. But as the value of chain affiliation decreases in aggregate, the fees charged to be a member of a chain may be forced to decrease as well, particularly for chains that target the limited service segment. In addition, as the quality of the individual property becomes more important and the reputation of the brand as a whole becomes less important, the free rider problem is lessened. Thus, contracts with a strong

[18] See also Lal (1990).

monetary incentive to maintain high quality should be less necessary and could be fazed out in settings where they produce inefficient outcomes.

Business format franchising is widely used across retail and service industries and the effects of online reputation mechanisms are likely to vary based on firm and market type. Several results in this study point to one possible mechanism explaining the declining premium associated with chain affiliation. At the low end of the quality spectrum, and in small markets or settings with little potential for repeat business, uncertainty is high and consumers exhibit risk aversion with respect to negative outcomes. This uncertainty and risk aversion likely explain much of the value of branding in those settings and as more information has become available through alternative channels, this value is significantly diminished. For these firms, increasing the amount of online word of mouth is associated with a substantial increase in revenue. For higher quality firms, the value associated with branding has been less affected by new sources of information, indicating it may stem more from loyalty and signaling specific amenities or distinguishing features. In the case of hotels, then, high quality brands might focus more efforts on developing distinctive offerings both at the chain-wide level and at individual properties.

In general, the increase in information available to consumers has significant implications for the future of umbrella branding. The spillover of reputation across products sold under the same brand should decrease, and with it the value of branding as a whole. Whether Chains should react to this decrease in spillovers by investing less in quality of individual products or whether they should invest more in individual product quality and less in brand reputation remains an open question beyond the scope of this paper. But the results here do suggest this is likely to vary over the average quality level of the brand as well as the type of market or setting they are found in.

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Figure 1: Share of Texas Hotels with Online Reviews

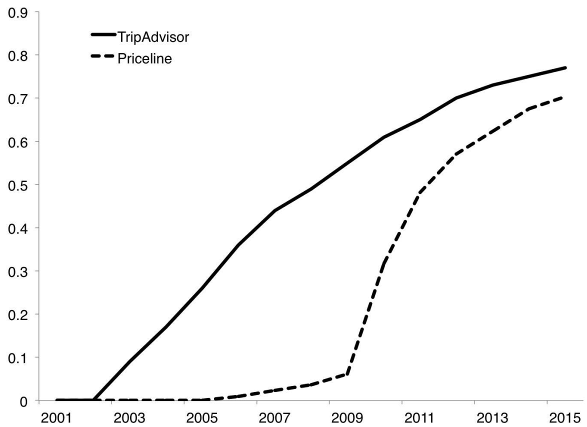


Figure 2: Average Number of Online Reviews per Hotel

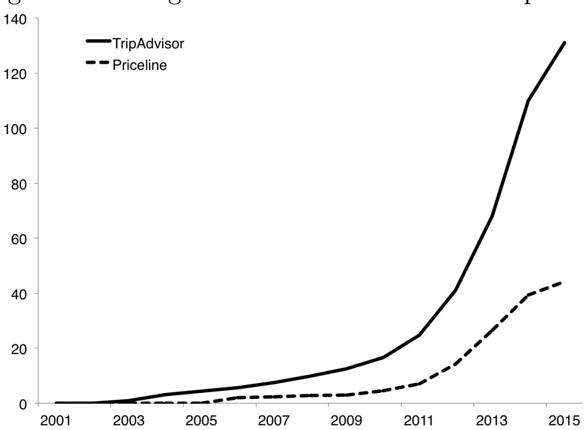
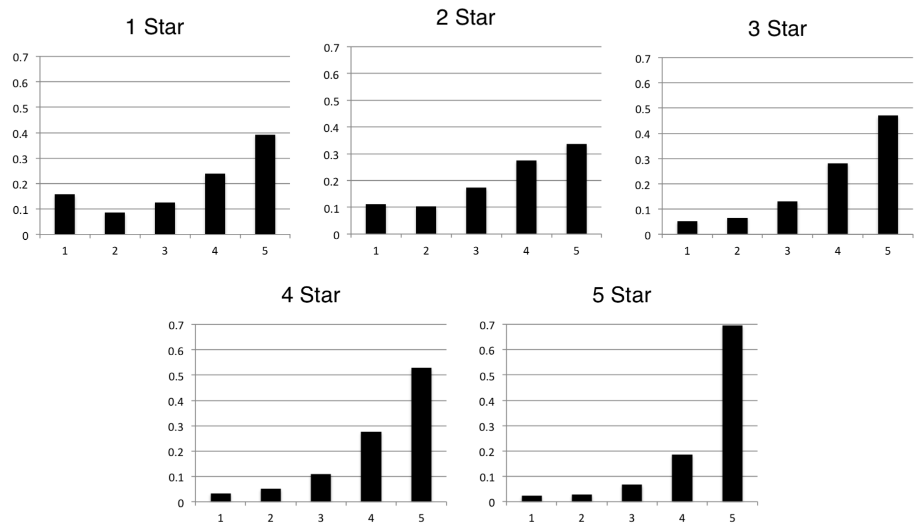
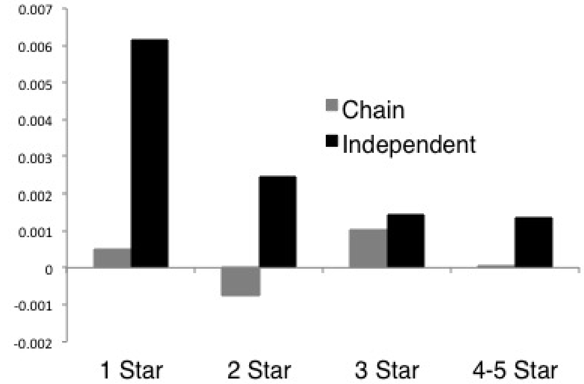


Figure 3: Distribution of TripAdvisor Reviews by Hotel Type



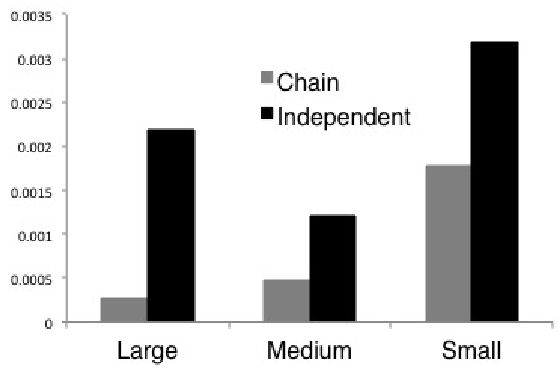
Note: The figure shows histograms of reviews for each quality level as defined by AAA stars. Within each AAA star level, I depict the share of reviews at each star level. N=382,556.

Figure 4: The Marginal Effect of Number of Reviews by AAA Rating



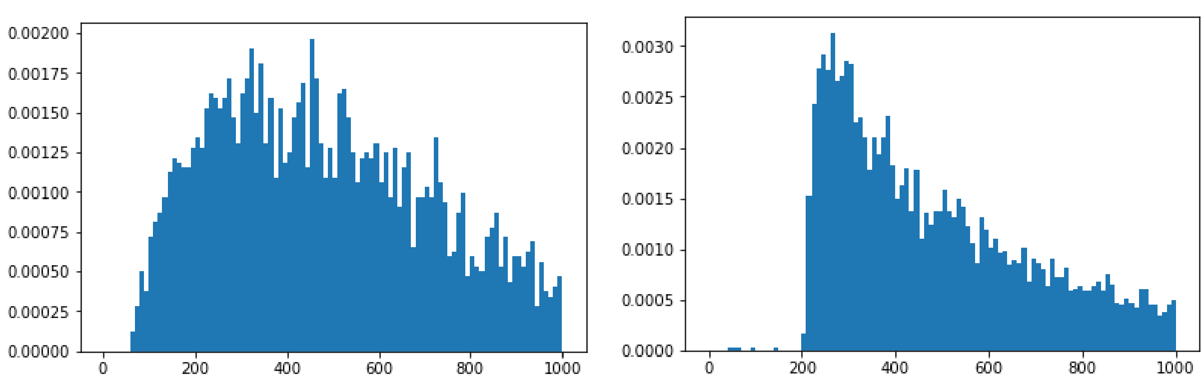
Note: This figure plots the coefficients from the regression described in equation 1 where number of reviews is interacted with AAA ratings. All independent firm coefficients are statistically significant at the 1% level. Only the coefficient on 3 star chain firms is significant.

Figure 5: The Marginal Effect of Number of Reviews by Market Size



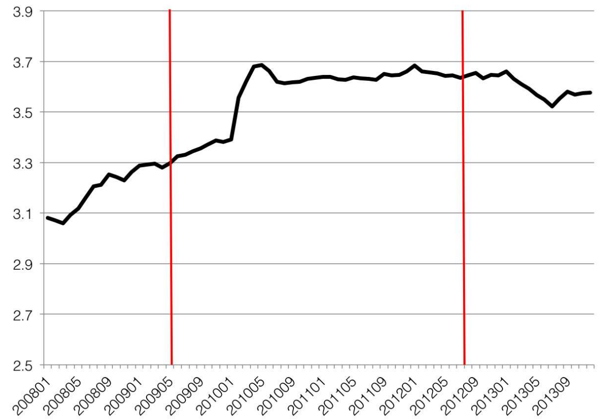
Note: This figure plots the coefficients from the regression described in equation 1 where number of reviews is interacted with market type. All coefficients are significant at the 5% level except for large market chains, which is not.

Figure 6: Histogram of TripAdvisor Review Lengths: July and August 2012



Note: These figures are histograms showing the distributions of TripAdvisor review lengths before and after the minimum length was changed to 200 characters in August 2012. The left figure is July 2012 and the right figure is August.

Figure 7: Average Monthly TripAdvisor Rating Over Time



Note: This chart shows the average TripAdvisor rating in each month from 2008-2013. The two lines represent the dates in which minimum review length policies were implemented.

Table 1: Hotel Revenue Summary Statistics

	Total	Std. Dev.
Number of Firms		
chain	2,902	
Independent	1,776	
★	604	
★★	740	
★★★	1,499	
★★★★	89	
★★★★★	6	
Entrants 2000-2013	2,112	
Exits 2000-2013	408	
Mean RevPar - 2013		
Total	$ 39.7	39.2
chain	$ 52.2	38.1
Independent	$ 28.8	44.6
★	$ 23.9	26.3
★★	$ 36.6	22.9
★★★	$ 66.9	34.9
★★★★	$ 129.3	52.9
★★★★★	$ 345.6	343.0

This table presents summary statistics on number of hotels by type in 2015 and average inflation-adjusted revenue per room per day (RevPar) by hotel type.

Figure 8: The Falling chain Premium

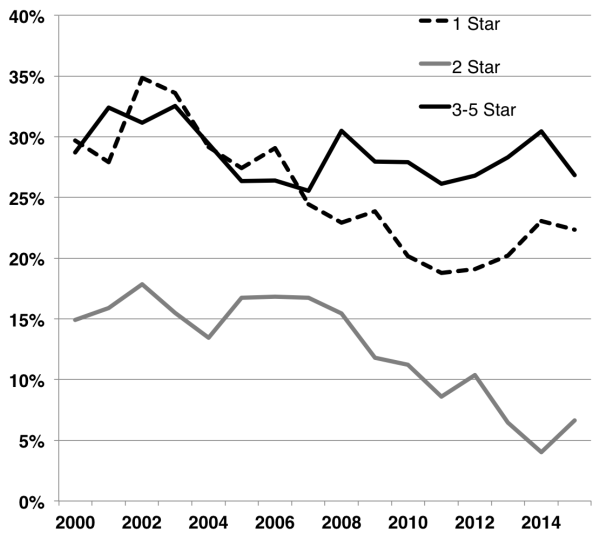


Figure 9: The Falling chain Premium

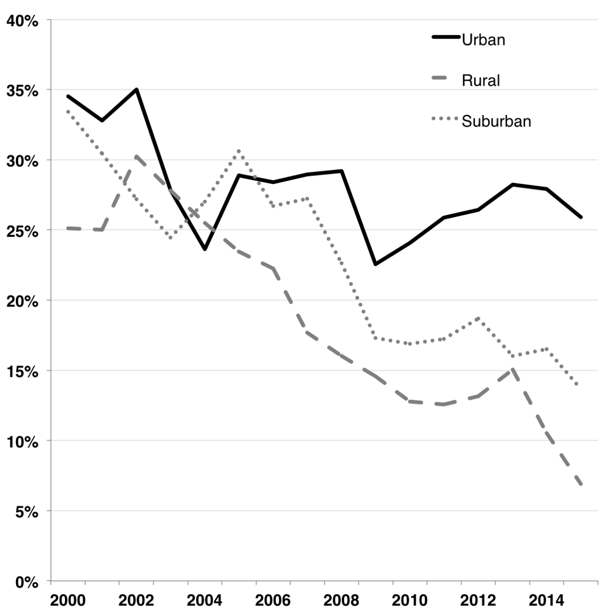


Figure 10: Chain Revenue Trend

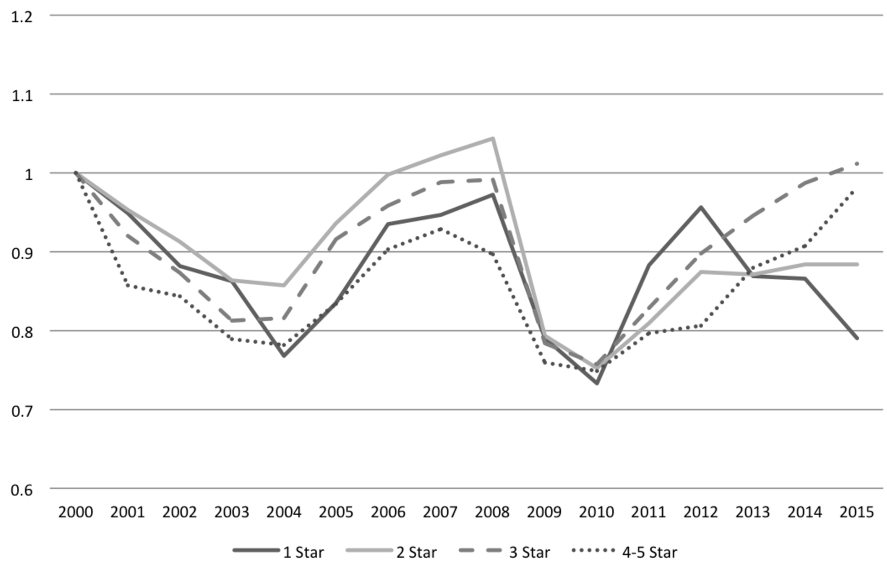


Figure 11: Unaffillated Revenue Trend

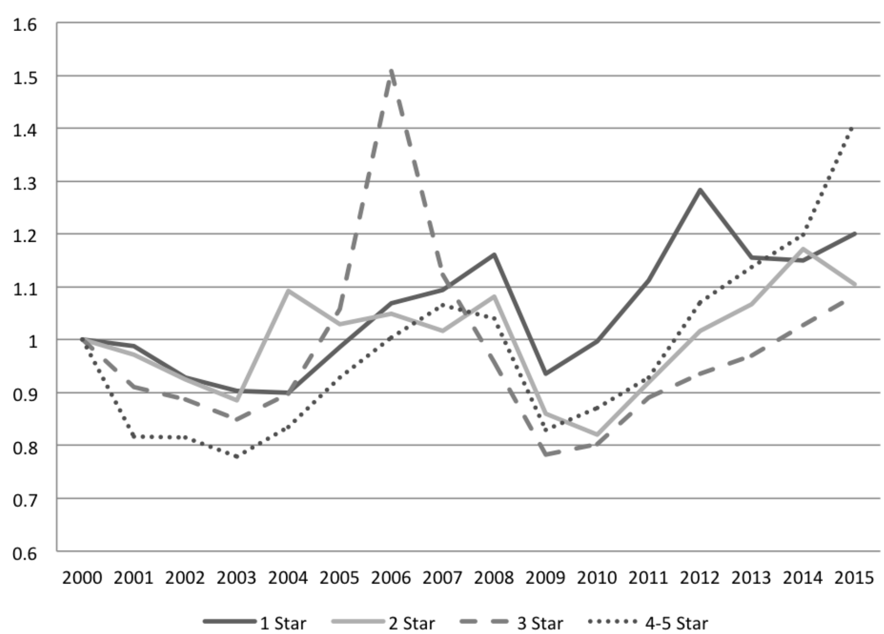
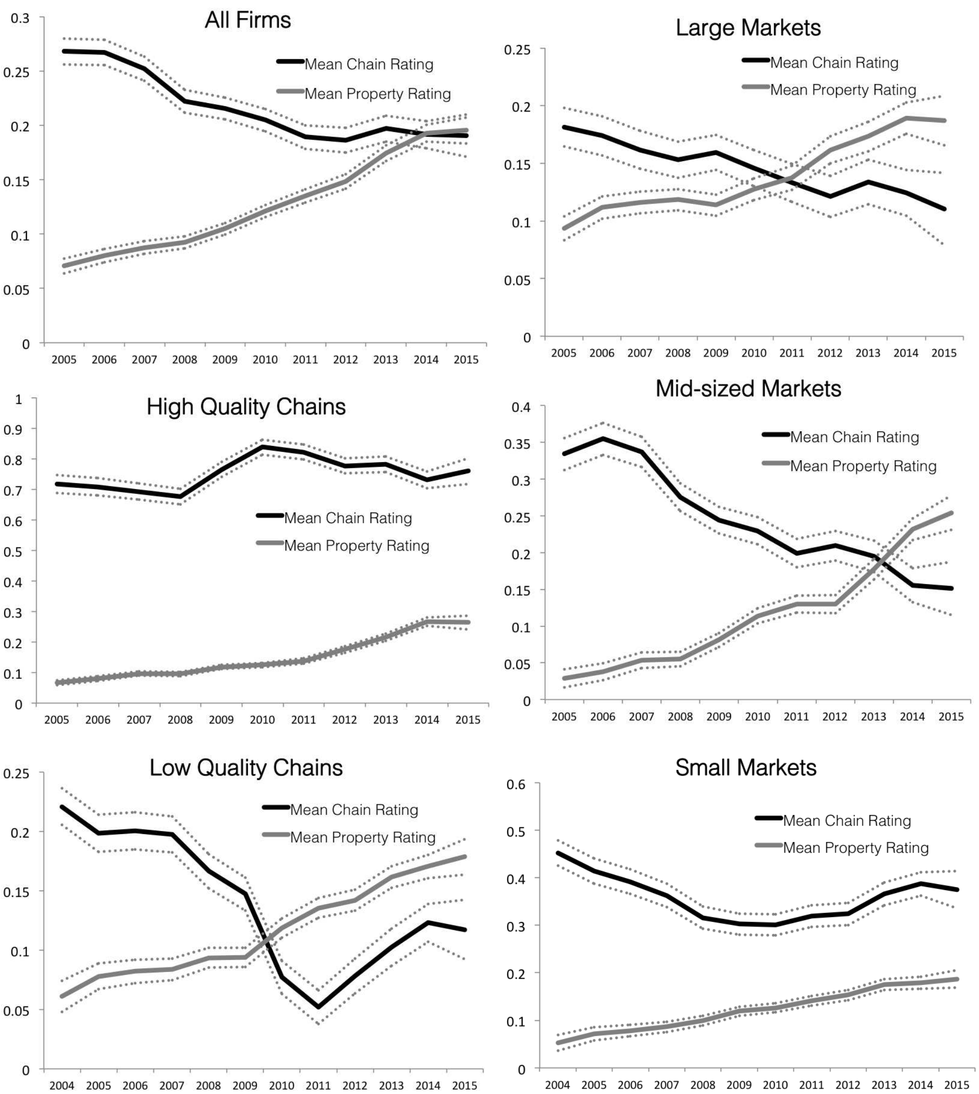


Figure 12: Increasing Importance of Outlet Ratings



Note: This figure plots the coefficients from a regression of log(RevPAR) on average chain-level ratings and outlet-level ratings interacted with year, along with firm and market characteristics and firm and time fixed effects. Low-quality chains are defined as those with 1 or 2 AAA stars, and high-quality chains as those with 3 or higher. 95% confidence intervals indicated with dotted lines.

Table 2: Chain Summary Statistics

Chain	Number of Outlets	Mean Rooms	Mean RevPar
Best Western	275	66.2	37.7
Holiday Inn Express	224	80.5	54.0
La Quinta	213	99.8	41.8
Comfort Inn	204	68.3	42.1
Super 8	159	57.6	29.9
Hampton Inn	157	87.7	58.9
Days Inn	142	66.5	26.7
Motel 6	136	94.1	24.3
America's Best Value Inn	88	62.8	20.3
Courtyard by Marriott	74	130.9	64.1
Quality Inn	72	90.5	31.1
Hilton Garden Inn	68	230.0	77.1
Holiday Inn	67	181.2	50.9
Ramada Inn	60	111.5	21.8
Fairfield Inn	60	94.9	53.1
Regency Inn	55	50.5	17.0
Candlewood Sutes	53	92.7	43.2
Residence Inn	53	112.7	77.9
Econo Lodge	47	51.9	22.4
Extended Stay	46	99.9	33.7
Hawthorn Suites	45	81.5	38.6
Marriott Hotel	44	385.8	86.9
Homewood Suites	43	103.9	73.0
Studio 6	41	105.2	27.6
Sleep Inn	37	66.8	37.1

This table presents summary statistics on hotel size and revenue RevPar for the 25 most common chains in all Texas markets.

Table 3: TripAdvisor.com Reviews in 2015

AAA Rating	★	★★	★★★	★★★★	★★★★★
chain					
Share of Firms Listed	.85	.93	.98	1	1
Mean # Reviews	19.3	44.9	82.8	452.7	521.8
Average Rating	2.75	3.41	4.01	4.11	4.48
Independent					
Share of Firms Listed	.49	.83	.89	1	1
Mean # Reviews	14.9	44.1	151.4	475.3	244.8
Average Rating	2.99	3.23	3.85	4.17	4.42

Table 4: Top Words Associated with Each Topic

Room	Service Issues	Chain/Business	General Quality	Location	Spanish
bed	desk	marriott	stay	area	de
night	would	guest	staff	pool	la
one	front	conference	great	small	e
door	day	event	clean	parking	el
bathroom	stay	meeting	breakfast	floor	que
floor	problem	team	nice	riverwalk	en
place	time	member	good	lobby	muy
stay	one	attention	friendly	water	da
didnt	service	westin	stayed	large	un
shower	told	detail	location	tv	para
front	back	staff	area	walk	por
desk	night	w	would	nice	con
dirty	check	property	comfortable	bar	al
first	could	hilton	place	coffee	lo
clean	called	banquet	service	river	und
next	manager	expect	restaurant	view	del
stayed	said	however	time	elevator	die
wall	went	group	helpful	lounge	se
water	asked	used	well	lot	bien
dont	reservation	hyatt	one	street	una
old	experience	quality	bed	antonio	le
towel	made	valet	night	restaurant	los
breakfast	go	need	pool	free	der
even	staff	outstanding	free	alamo	no
work	call	level	always	outside	desayuno
good	checked	grand	food	comfortable	excelente
smell	minute	courtyard	excellent	flat	si
carpet	never	driskill	recommend	valet	quarto
air	didnt	ball	really	door	todo
ac	guest	fairmont	close	window	um
bad	next	business	price	side	pero
never	also	party	best	food	este
time	arrived	brother	enjoyed	night	mi
sheet	customer	held	day	across	uma
people	took	function	again	modern	et
back	know	interaction	family	little	esta
need	make	stadium	definitely	well	war
motel	another	work	get	beautiful	personal
looked	came	star	like	balcony	ma
toilet	booked	four	inn	building	man
lot	hour	competition	desk	table	zimmer
hot	left	flag	everything	park	habitaciones
tv	first	year	front	light	ist
sleep	morning	incidental	little	size	im
morning	charge	better	trip	noise	muito
noise	phone	car	back	huge	dia
tub	card	concierge	quiet	drink	como
problem	say	parking	need	hot	com
better	two	facility	wonderful	much	den
31.30%	26.03%	1.37%	25.71%	12.25%	2.05%

This table presents the top 50 words associated with each topic determined by the LDA topics analysis of all reviews. The bottom row shows the total share of reviews associated with that topic.

Table 5: Regressor Summary Statistics

	Mean	Std Dev	Min	Max	Median	Frequency	Unit of Obs.	Source
Firm Variables								
RevPar	35.49	32.46	0	550.6	26.68	Monthly	Property	Texas Comptroller
AAA Rating	2.27	.86	1	5	2	Annual	Property	AAA
Chain Affiliation	.58	.49	0	1	1	Monthly	Property	Combination of sources
Capacity	86.05	91.48	20	1840	62	Monthly	Property	Texas Comptroller
Age	10.40	7.05	0	56	9	Monthly	Property	Texas Comptroller
Under renovation	.08	.27	0	1	0	Monthly	Property	TripAdvisor and Priceline
Recently Renovated	.36	.47	0	1	0	Monthly	Property	TripAdvisor and Priceline
County Level Firms								
Chains	50.89	70.92	0	211	14	Monthly	County	Texas Comptroller
Independents	31.05	51.47	0	179	7	Monthly	County	Texas Comptroller
TripAdvisor Data (2015)								
Mean Rating	3.56	.844	1	5	3.78	Monthly	Property	TripAdvisor
Standard Deviation of Ratings	1.12	.31	0	2	1.15	Monthly	Property	TripAdvisor
Number of Reviews	101.41	205.96	0	3166	40	Monthly	Property	TripAdvisor
Number of Characters	62924.18	147068.7	0	2452923	23528	Monthly	Property	TripAdvisor
Market Competitor Reviews	189.24	263.42	0	797	50	Monthly	City	TripAdvisor
Mean of Last 5 Ratings	3.59	.95	1	5	3.8	Monthly	Property	TripAdvisor
Priceline Data (2015)								
Mean Rating	7.19	1.65	1	10	7.61	Monthly	Property	Priceline
Standard Deviation of Ratings	3.54	.73	0	4.5	3.75	Monthly	Property	Priceline
Number of Reviews	31.05	45.07	0	318	15	Monthly	Property	Priceline
Number of Characters	65317	957.33	0	676052	10556	Monthly	Property	Priceline
Market Competitor Reviews	3324.78	4783.11	0	14517	631	Monthly	City	Priceline
Mean of Last 5 Ratings	7.20	1.84	1	10	7.60	Monthly	Property	Priceline
Mean of Last Month Ratings	3.57	1.24	1	5	4	Monthly	Property	TripAdvisor and Priceline
Unique terms	2097.92	2763.75	0	30333	1397	Monthly	Property	TripAdvisor and Priceline
Recent review	.29	.46	0	1	0	Monthly	Property	TripAdvisor and Priceline
Number of Short Reviews	57.30	110.48	0	2184	22	Monthly	Property	TripAdvisor and Priceline
Number of Medium Reviews	28.56	61.98	0	925	11	Monthly	Property	TripAdvisor and Priceline
Number of Long Reviews	12.27	32.26	0	571	3	Monthly	Property	TripAdvisor and Priceline
Text Data (2015)								
Topic 1 Proportion (Room)	.19	.06	0	.65	.19	Monthly	Property	TripAdvisor and Priceline
Topic 2 Proportion (Service)	.28	.16	0	.95	.24	Monthly	Property	TripAdvisor and Priceline
Topic 3 Proportion (General)	.32	.12	0	.66	.34	Monthly	Property	TripAdvisor and Priceline
Topic 4 Proportion (Location)	.09	.06	0	.45	.08	Monthly	Property	TripAdvisor and Priceline
Topic 5 Proportion (Chain)	.06	.06	0	.63	.04	Monthly	Property	TripAdvisor and Priceline
Topic 6 Proportion (Spanish)	.03	.06	0	.98	.01	Monthly	Property	TripAdvisor and Priceline
Topic 1 High Rating Share (Room)	.56	.27	0	1	.56	Monthly	Property	TripAdvisor and Priceline
Topic 2 High Rating Share (Service)	.18	.19	0	1	.14	Monthly	Property	TripAdvisor and Priceline
Topic 3 High Rating Share (General)	.90	.15	0	1	.95	Monthly	Property	TripAdvisor and Priceline
Topic 4 High Rating Share (Location)	.95	.16	0	1	1	Monthly	Property	TripAdvisor and Priceline
Topic 5 High Rating Share (Chain)	.88	.26	0	1	1	Monthly	Property	TripAdvisor and Priceline
Topic 6 High Rating Share (Spanish)	.67	.37	0	1	.80	Monthly	Property	TripAdvisor and Priceline

Note: This table presents summary statistics on market and firm characteristics, where market refers to county and firm refers to a property operated continually at a specific address. Statistics for TripAdvisor and Priceline data are from 2015 only.

Table 6: Effects of Online Reputation on Chain and Independent Hotel Revenue

	(1)	(2)	(3)	(4)
Lagged # Reviews	-0.0000080			
	(0.0001)			
Lagged # Reviews X Independent	0.0012***			
	(0.0003)			
Lagged # Characters		-0.000000025		
		(0.0000)		
Lagged # Characters X Independent		0.0000016***		
		(0.0000)		
Lagged # Unique Words			-0.0000046	
			(0.0000)	
Lagged # Unique Words X Independent			0.000037**	
			(0.0000)	
Recent Review				0.000075
				(0.0001)
Recent Review X Independent				0.00030*
				(0.0001)
Chain Affiliated	0.069	0.070	0.070	0.069
	(0.0564)	(0.0564)	(0.0564)	(0.0564)
Independent Competitors	0.0010*	0.0010*	0.0010*	0.0010*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Chain Competitors	-0.00059	-0.00059	-0.00060	-0.00059
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Age	-0.0065	-0.0070*	-0.0071*	-0.0070*
	(0.0035)	(0.0031)	(0.0030)	(0.0031)
log(Capacity)	-1.07***	-1.07***	-1.07***	-1.07***
	(0.0675)	(0.0675)	(0.0675)	(0.0675)
Mean of Competitor RevPar	0.0069***	0.0069***	0.0069***	0.0069***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
1 AAA Star	-0.0074*	-0.0076*	-0.0079*	-0.0075*
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
2 AAA Star	0.018***	0.018***	0.018***	0.018***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)
3 AAA Star	0.049***	0.049***	0.049***	0.049***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
4 AAA Star	0.085***	0.085***	0.087***	0.083***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
5 AAA Star	0.13***	0.13***	0.13***	0.13***
	(0.0099)	(0.0098)	(0.0098)	(0.0099)
TripAdvisor Rating	0.013***	0.013***	0.013***	0.013***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Priceline Rating	0.0063***	0.0063***	0.0063***	0.0063***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Mean of Last 5 on TA	-0.0069***	-0.0070***	-0.0070***	-0.0070***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Mean of Last 5 on PL	-0.0048***	-0.0048***	-0.0048***	-0.0048***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
TripAdvisor Std Dev.	0.0036	0.0037	0.0036	0.0037
	(0.0042)	(0.0042)	(0.0042)	(0.0042)
Priceline Std Dev.	0.0036**	0.0036**	0.0036**	0.0036**
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Mean of Previous Month Ratings	-0.0017*	-0.0018*	-0.0018*	-0.0018*
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Lagged Log(RevPar)	-0.095***	-0.095***	-0.094***	-0.095***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Topic 1 Proportion (Room)	-0.032	-0.032	-0.032	-0.032
	(0.0184)	(0.0184)	(0.0184)	(0.0184)
Topic 2 Proportion (Service)	-0.024*	-0.024*	-0.024*	-0.023*
	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Topic 3 Proportion (General)	-0.035	-0.035	-0.035	-0.035
	(0.0227)	(0.0227)	(0.0227)	(0.0227)
Topic 4 Proportion (Location)	-0.058	-0.058	-0.058	-0.057
	(0.0391)	(0.0390)	(0.0391)	(0.0390)
Topic 5 Proportion (Brand)	0.089*	0.089*	0.090*	0.089*
	(0.0407)	(0.0407)	(0.0407)	(0.0407)
Topic 6 Proportion (Spanish)	0.0038	0.0036	0.0039	0.0036

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)
	(0.0494)	(0.0494)	(0.0494)	(0.0494)
Topic 1 High Rating Share (Room)	0.028***	0.028***	0.028***	0.028***
	(0.0081)	(0.0081)	(0.0081)	(0.0081)
Topic 2 High Rating Share (Service)	0.020**	0.020**	0.019**	0.021**
	(0.0073)	(0.0073)	(0.0073)	(0.0073)
Topic 3 High Rating Share (General)	0.0056	0.0061	0.0062	0.0057
	(0.0082)	(0.0082)	(0.0082)	(0.0082)
Topic 4 High Rating Share (Location)	0.010	0.011	0.0098	0.011
	(0.0109)	(0.0109)	(0.0110)	(0.0110)
Topic 5 High Rating Share (Brand)	0.016	0.017	0.017	0.017
	(0.0124)	(0.0124)	(0.0124)	(0.0124)
Topic 6 High Rating Share (Spanish)	0.0052	0.0051	0.0049	0.0050
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Under Renovation	-0.016	-0.015	-0.014	-0.014
	(0.0116)	(0.0100)	(0.0100)	(0.0100)
Recently Renovated	0.0016	0.0022	0.0016	0.0026
	(0.0098)	(0.0098)	(0.0098)	(0.0098)
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes
Franchisee FE	Yes	Yes	Yes	Yes
Month X Market Type	Yes	Yes	Yes	Yes
Observations	241418	241418	241418	241418
R^2	0.268	0.268	0.268	0.268

Note: This table includes additional measures of information that incorporate the text of reviews. In every case the dependent variable is Log(RevPar). Column (1) is the primary specification from the paper and is included as a benchmark. Column (2) still includes the lagged number of reviews but adds the number of total characters for chain and independent hotels separately. Column (3) adds the total number of unique words posted in reviews. This specification excludes hotels with fewer than 5 reviews posted. Column (4) includes a dummy variable for whether or not the hotel had a review posted in the most recent month.

Table 7: Top Words Classified by Firm Type

Distinctive to Chain	Ratio	Distinctive to Independent	Ratio
shuttle	17.78	waterpark	20.12
I-20	15.92	Texan	19.03
Marcos	7.82	Fredericksburg	16.88
airport	7.819999998	lodge	12.62
DFW	7.6	resort	12.51
flight	7.48	historic	12.02
I-35	7.018666667	slides	9.83
Hair	5.88	condo	9.70
Convenient	4.9	quaint	8.64
Airport	4.8	kitchen	7.84
accent	4.54	Bend	7.50
Starbucks	4.54	trains	7.48
Lost	4.24	charm	7.34
freeway	4.06	boardwalk	7.33
MOTEL	3.86	Ranch	7.30
professionally	3.56	Main	7.18
terminal	3.44	fishing	7.11
mall	3.44	slide	6.92
exercise	3.36	quest	6.57
rudely	3.34	balcony	6.50
reliable	3.32	seawall	6.48
stored	3.28	dinner	6.12
Mansion	3.18	fun	5.98
knowledge	3.14	Route 66	5.73
lacked	3.1	Harbor	5.70
shaped	2.98	Park	5.59
Desk	2.94	baths	5.51
Patel	2.74	beach	5.38
viewed	2.68	horse	5.34
plane	2.66	Lodge	5.30
Showers	2.66	ghost	5.29
grimy	2.58	beautiful	5.23
nonsmoking	2.58	blast	5.06
laminate	2.56	railroad	4.97
Ikea	2.56	Palomar	4.96
staffed	2.54	restaurant	4.94
Barbara	2.46	antique	4.92
shift	2.46	bend	4.86
perks	2.44	steak	4.78
Talk	2.42	charming	4.58
bus	2.4	fireplace	4.32
Needed	2.4	fountain	4.31
leak	2.32	relaxing	4.30
toaster	2.3	Restaurant	4.29
Interstate	2.2	park	3.64
layover	1.94	Owner	3.63
purposes	2.22	cruise	3.53
drawers	2.2	West	3.53

This table presents the top 50 words distinctly associated with one firm type versus the other. The results come from a Naive Bayes Classification on the full set of hotel reviews where the outcome variable being matched is chain versus independent and AAA star rating is controlled for. The ratio presented is the average ratio across training runs of how much more frequently a word is associated with the given firm type. The analysis excludes brand names such as "Marriott" which would otherwise occupy a large share of column 1.

Table 8: The Revenue Premium of Chain Affiliation Over Time

	(1) All Firms	(2) All Firms	(3) Rural	(4) Urban	(5) Suburban	(6) 1 Star	(7) 2 Star	(8) 3 Star
Independent Competitors	0.001	0.000	0.013*	-0.001	-0.001	0.006	0.001	0.001
	(0.001)	(0.001)	(0.005)	(0.001)	(0.003)	(0.005)	(0.001)	(0.001)
chain Competitors	-0.001***	-0.001***	-0.019***	-0.001	-0.003	-0.004*	-0.001*	-0.000
	(0.000)	(0.000)	(0.004)	(0.000)	(0.002)	(0.002)	(0.001)	(0.000)
Age	0.046	0.046	-0.099**	0.392***	0.010	-0.097	-0.135	0.004
	(0.037)	(0.037)	(0.036)	(0.021)	(0.022)	(0.156)	(0.109)	(0.049)
log(Capacity)	-0.843***	-0.846***	-0.794***	-0.942***	-0.846***	-0.953***	-0.767***	-0.947***
	(0.050)	(0.050)	(0.074)	(0.059)	(0.115)	(0.090)	(0.114)	(0.056)
TA Stars	0.038***	0.039***	0.015	0.061***	0.042***	0.007	0.024**	0.033***
	(0.005)	(0.005)	(0.008)	(0.007)	(0.009)	(0.017)	(0.008)	(0.007)
# TA Reviews	0.000***	0.000***	0.001***	0.000***	0.000	0.000	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Listed on TA.com	-0.079***	-0.063***	-0.002	-0.110***	-0.080*	-0.018	-0.063*	0.007
	(0.018)	(0.018)	(0.033)	(0.026)	(0.035)	(0.058)	(0.030)	(0.029)
Mean Competitor RevPAR	0.010***	0.010***	0.008***	0.015***	0.010***	0.008***	0.011***	0.010***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
1 AAA Star	-0.893	-0.892	0.536					
	(0.878)	(0.884)	(0.700)					
2 AAA Star	-1.028	-1.020	0.451	-3.842***	-0.338			
	(0.861)	(0.867)	(0.690)	(0.234)	(0.593)			
3 AAA Star	-0.982	-0.986	0.563	-4.059***	-0.134			
	(0.897)	(0.903)	(0.682)	(0.227)	(0.513)			
4 AAA Star	-0.820	-0.845		-5.146***	-0.399			
	(0.842)	(0.850)		(0.295)	(0.610)			
Chain	0.252***							
	(0.031)							
Chain X 2000		0.315***	0.251***	0.339***	0.331***	0.296***	0.147*	0.281***
		(0.033)	(0.051)	(0.058)	(0.072)	(0.084)	(0.064)	(0.068)
Chain X 2001		0.298***	0.250***	0.322***	0.301***	0.278***	0.157*	0.303***
		(0.033)	(0.050)	(0.060)	(0.071)	(0.083)	(0.066)	(0.071)
Chain X 2002		0.311***	0.302***	0.345***	0.269***	0.347***	0.177**	0.302***
		(0.033)	(0.050)	(0.059)	(0.070)	(0.083)	(0.066)	(0.068)
Chain X 2003		0.269***	0.278***	0.275***	0.243***	0.335***	0.153*	0.328***
		(0.032)	(0.049)	(0.057)	(0.069)	(0.081)	(0.065)	(0.067)
Chain X 2004		0.252***	0.255***	0.235***	0.271***	0.291***	0.134*	0.302***
		(0.032)	(0.050)	(0.056)	(0.068)	(0.079)	(0.064)	(0.069)
Chain X 2005		0.271***	0.234***	0.290***	0.309***	0.274**	0.169*	0.279***
		(0.032)	(0.049)	(0.056)	(0.065)	(0.087)	(0.068)	(0.067)
Chain X 2006		0.258***	0.223***	0.287***	0.272***	0.292***	0.171*	0.276***
		(0.032)	(0.050)	(0.056)	(0.065)	(0.087)	(0.069)	(0.068)
Chain X 2007		0.240***	0.177***	0.294***	0.278***	0.246**	0.170*	0.283***
		(0.032)	(0.049)	(0.056)	(0.066)	(0.087)	(0.069)	(0.065)
Chain X 2008		0.228***	0.160**	0.298***	0.234***	0.231**	0.158*	0.344***
		(0.032)	(0.049)	(0.057)	(0.068)	(0.084)	(0.065)	(0.070)
Chain X 2009		0.193***	0.146**	0.230***	0.180**	0.240**	0.121	0.335***
		(0.033)	(0.050)	(0.058)	(0.068)	(0.091)	(0.067)	(0.074)
Chain X 2010		0.187***	0.128*	0.245***	0.175**	0.203*	0.114	0.356***
		(0.033)	(0.051)	(0.058)	(0.068)	(0.086)	(0.070)	(0.078)
Chain X 2011		0.191***	0.126*	0.262***	0.178**	0.189	0.086	0.330***
		(0.034)	(0.054)	(0.059)	(0.068)	(0.097)	(0.076)	(0.072)
Chain X 2012		0.206***	0.132*	0.265***	0.192**	0.193*	0.104	0.331***
		(0.034)	(0.055)	(0.059)	(0.068)	(0.096)	(0.082)	(0.070)
Chain X 2013		0.227***	0.151**	0.280***	0.164*	0.204*	0.063	0.353***
		(0.034)	(0.055)	(0.059)	(0.068)	(0.096)	(0.078)	(0.071)
Chain X 2014		0.213***	0.105	0.277***	0.169*	0.232*	0.039	0.374***
		(0.035)	(0.056)	(0.060)	(0.072)	(0.107)	(0.081)	(0.075)
Chain X 2015		0.194***	0.069	0.257***	0.141	0.225*	0.065	0.332***
		(0.036)	(0.058)	(0.061)	(0.073)	(0.099)	(0.088)	(0.073)
Property FE	Y	Y	Y	Y	Y	Y	Y	Y
Owner FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
N	723809	723809	272274	261315	156046	100707	121139	190006

This table presents estimates of the chain premium as a percent of firm revenue, interacted with year, by firm type and market type. In all columns the dependent variable is log(RevPAR). Standard errors are robust and clustered at the property level.

A Appendix A

This Appendix presents robustness checks on the results in section 3. The object of interest in this section is the effect on revenue of the interaction between the amount of information in online reputation mechanisms and whether the firm is chain or independent. The argument that this interaction is measured correctly is based on a broad set of controls for potential endogeneity.

Ultimately, there are six potential sources of bias in equation 1. (1) Property-level factors that impact revenue may be correlated with number of reviews. (2) Market level factors may correlate with both revenues and number of reviews. (3) Firms may change ownership or management, leading to changes in both revenues and reviews. (4) Unobserved quality factors may change over time, impacting both revenue and number of reviews. (5) Chain-wide marketing actions that vary over time may impact both revenue and the number of reviews posted and may persist over many periods and (6) online WOM may be correlated with offline WOM.

I eliminate concerns 1, 2, and 3 by including property and owner fixed effects to eliminate time-invariant quality and service features, market level month and year dummies to account for time trends and seasonality. For concern 4, I include a a set of eight variables that measure time-varying quality using information from online quality ratings.

Concern 5 is that advertising campaigns might increase both revenue and number of reviews over a medium-term period. I test for this using average chain partner RevPar. Because marketing activities are coordinated at the chain level and because activities like advertising have spillovers across chain partners, controlling for average chain partner performance should capture any medium-term demand driven by marketing. Results from including this can be seen in column 6 of Table 9. Including this measure does not change the main results. In addition, effects of advertising campaigns should be captured by the lagged dependent variable.

Concern 6 is that offline word of mouth is correlated with ownline word of mouth and is likely to affect revenues. In addition to including time dummies to capture any trends, I also test for this concern by including the number of reviews of chain partners from outside the focal hotel's market. The result of this test can be seen in column 5 of Table 9. The coefficient on number of reviews of chain partners is very close to zero and not significant. Including this measure also seems to strengthen the main empirical result, as it causes the coefficient on the number of reviews for independent hotels to increase.

After including these controls, there still exists potential simultaneity in short term demand shocks that could generate upward bias in the coefficient on number of reviews. While this would not necessarily bias the interaction term that is the object of interest, it is still worth testing to rule out bias of this sort. The concern is that after controlling for all the factors described above there is serial correlation in the remaining idiosyncratic component of revenue. This type of serial correlation can be tested for. The test follows Wooldridge (2002) and accounts for fixed effects such as the property fixed effects I include throughout. The results from these tests are shown in Table 10. The error term after accounting only for property fixed effects and basic characteristics such as age and capacity shows strong serial correlation. Including month dummies to account for seasonality reduces serial correlation but it is still significant. Adding mean competitor RevPar as a measure of market level shocks significantly reduces serial correlation to the extent that it is not significant and adding further controls for seasonality, short term quality changes, and the lagged dependent variable go even further to rule out a significant serial correlation in the remaining idiosyncratic term.

As a further robustness check to rule out serial correlation in demand or in time-varying unobserved quality, I use as instruments additional lags of number of reviews. This is suggested by Wooldridge (2002) as a way of taking advantage of the sequential nature of the key variable. The number of reviews this month is the sum of the number last month plus the number posted in the interim. If the key variable is one month lagged number of reviews, prior lags of number of reviews is highly (positively) correlated with this and much less correlated with current revenue. The further back in time we lag, the more true this becomes. In theory, this could apply to very old lags who would have no direct effect on revenue but would still be correlated with the current number of reviews. In practice, we must temper our interpretation of the coefficients in acknowledgement that there is still possibly a direct effect in cases where hotel stays are booked well in advance. In other words, for a 9-month lagged number of reviews, we would expect a small but theoretically positive effect on revenue if some consumers view reviews and book 9 months in advance. We would expect a clear and direct positive relationship the 9 month lag and current value of number of reviews, since this variable is cumulative by definition. Since property fixed effects account for time-invariant hotel characteristics the direct effect of the lagged variable on revenue is the main concern with these instruments.

I estimate three examples of this type of IV separately using GMM, and results are shown in Table 11. Column 1 shows the baseline result used in the paper, column 2 uses the 6 month lag as an IV, column 3 uses the 9 month lag, and column 4 uses the 12 month lag.[19]

While this deals effectively with serial correlation in demand, a second issue with this approach is that the lagged variable might still be correlated with time-varying omitted quality. To the extent that this is true, these lagged variables function as "imperfect instrumental variables" (IIV) as discussed by Nevo and Rosen (2012), Conley et al. (2012), Kolesar et al. (2015), and others, meaning that the IV's are not completely uncorrelated with the unobserved term but may still be of some use. In particular, the instruments still allow partial identification of the parameter of interest. As described in Nevo and Rosen (2012), this type of IV can still be useful when "the correlation between the instrumental variable and the error term has the same sign as the correlation between the endogenous regressor and the error term and that the instrumental variable is less correlated with the error term than is the endogenous regressor".

If the key variable is one month lagged number of reviews, prior lags of number of reviews is highly (positively) correlated with this and much less correlated with the current omitted variable. I implement the approach described in section 3c of Nevo and Rosen (2012) and construct bounds using the results from 4 instruments: the 6 month lag of number of reviews, the 9 month lag, and the 12 month lag, and the difference

[19]The choice of 6, 9, and 12 months as the lags is admittedly arbitrary but testing other lags did not show any different results.

between the 6 and 12 month lags. This last IV is equivalent to the number of reviews posted between 6 and 12 months in the past and provides a plausible lower bound for the effect of interest. The results from this IV are shown in column 5. The bounds around the interaction effect of interest are [.0007, .0026]. Again this is consistent with the result using no instruments.

Table 9: Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged # Reviews X Chain (Total)	0.000727***			0.000713***	0.000621***	0.000734***
	(0.000136)			(0.000136)	(0.000141)	(0.000136)
Lagged # Reviews X Independent (Total)	0.00166***			0.00165***	0.00274***	0.00153***
	(0.000243)			(0.000243)	(0.000267)	(0.000243)
Lagged # Reviews X Chain (Priceline)		0.0000695				
		(0.000308)				
Lagged # Reviews X Independent (Priceline)		0.000160				
		(0.000923)				
Lagged # Reviews X Chain (TripAdvisor)			0.00102***			
			(0.000169)			
Lagged # Reviews X Independent (TripAdvisor)			0.00213***			
			(0.000275)			
Lagged Market # Reviews				-0.000218*		
				(0.000102)		
Lagged Chain partner # Reviews					0.00000466	
					(0.00000441)	
Mean Chain Partner RevPar						.00445***
						(.00013)
Chain	0.0660	0.0669	0.0661	0.0658	0.0702	-0.122*
	(0.0563)	(0.0563)	(0.0563)	(0.0562)	(0.0563)	(0.0564)
Independent Competitors	0.000862	0.000897*	0.000861	0.000904*	0.000828	0.000690
	(0.000441)	(0.000441)	(0.000441)	(0.000440)	(0.000440)	(0.000441)
Chain Competitors	-0.000561	-0.000592	-0.000565	-0.000625	-0.000517	-0.000744*
	(0.000335)	(0.000336)	(0.000335)	(0.000337)	(0.000335)	(0.000333)
Age	-0.00715*	-0.00805***	-0.00782***	-0.00716*	-0.00586	-0.00324
	(0.00289)	(0.00235)	(0.00237)	(0.00288)	(0.00369)	(0.00880)
Log(Capacity)	-1.078***	-1.079***	-1.078***	-1.078***	-1.072***	-1.076***
	(0.0692)	(0.0693)	(0.0692)	(0.0692)	(0.0674)	(0.0691)
Mean Competitor RevPAR	0.00695***	0.00695***	0.00695***	0.00695***	0.00690***	0.00685***
	(0.000298)	(0.000298)	(0.000298)	(0.000298)	(0.000296)	(0.000294)
Lagged Log(Revpar)	-0.0859***	-0.0851***	-0.0860***	-0.0859***	-0.0994***	-0.0843***
	(0.00184)	(0.00182)	(0.00184)	(0.00184)	(0.00211)	(0.00184)
1 AAA Star	-0.00560	-0.00597	-0.00569	-0.00558	-0.0131***	-0.00494
	(0.00331)	(0.00331)	(0.00331)	(0.00331)	(0.00341)	(0.00331)
2 AAA Star	0.0207***	0.0213***	0.0207***	0.0207***	0.0194***	0.0204***
	(0.00166)	(0.00166)	(0.00166)	(0.00166)	(0.00175)	(0.00165)
3 AAA Star	0.0605***	0.0612***	0.0605***	0.0605***	0.0409***	0.0613***
	(0.00190)	(0.00190)	(0.00190)	(0.00190)	(0.00192)	(0.00189)
4 AAA Star	0.103***	0.109***	0.102***	0.103***	0.0913***	0.106***
	(0.00380)	(0.00377)	(0.00379)	(0.00380)	(0.00419)	(0.00376)
5 AAA Star	0.157***	0.162***	0.156***	0.158***	0.154***	0.157***
	(0.00988)	(0.00980)	(0.00993)	(0.00989)	(0.0138)	(0.00989)
TripAdvisor Rating	0.0150***	0.0151***	0.0150***	0.0150***	0.0147***	0.0147***
	(0.00245)	(0.00245)	(0.00245)	(0.00245)	(0.00244)	(0.00245)
Priceline Rating	0.00635***	0.00621***	0.00627***	0.00634***	0.00618***	0.00635***
	(0.00165)	(0.00165)	(0.00165)	(0.00165)	(0.00164)	(0.00165)
Mean of Last 5 on TA	-0.00720***	-0.00729***	-0.00717***	-0.00717***	-0.00722***	-0.00694***
	(0.00188)	(0.00188)	(0.00188)	(0.00188)	(0.00188)	(0.00188)
Mean of Last 5 on PL	-0.00483**	-0.00471**	-0.00479**	-0.00482**	-0.00480**	-0.00479**
	(0.00147)	(0.00147)	(0.00147)	(0.00147)	(0.00147)	(0.00147)
TripAdvisor Std Dev.	0.00136	0.00105	0.00145	0.00137	0.00176	0.000998
	(0.00422)	(0.00422)	(0.00422)	(0.00422)	(0.00420)	(0.00419)
Priceline Std Dev.	0.00695**	0.00689**	0.00690**	0.00693**	0.00667**	0.00675**
	(0.00227)	(0.00227)	(0.00227)	(0.00227)	(0.00226)	(0.00226)
Mean of Previous Month Ratings	-0.00188**	-0.00188**	-0.00188**	-0.00189**	-0.00193**	-0.00181*
	(0.000723)	(0.000723)	(0.000723)	(0.000723)	(0.000721)	(0.000719)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Franchisee FE	Yes	Yes	Yes	Yes	Yes	Yes
Month X Market Type	Yes	Yes	Yes	Yes	Yes	Yes
Observations	241418	241418	241418	241418	241418	241418

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents a set of robustness tests for the main parameter of interest, the marginal effect of lagged # of reviews on independent versus chain hotels. In every case the dependent variable is Log(RevPar). Column (1) contains the primary specification as a benchmark. Column (2) uses only the number of Priceline reviews. Column (3) uses only the number of TripAdvisor reviews. Column (4) includes the total number of reviews of competing hotels in the same market where market is defined as city. Column (5) includes the total number of reviews of hotels in the same chain or chain as the hotel of interest. Column (6) includes as a control mean RevPar of hotels in the same chain or chain as the hotel of interest.

Table 10: Serial Correlation Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Chain	x	x	x	x	x	x	x
# Competitors	x	x	x	x	x	x	x
Age	x	x	x	x	x	x	x
Log(Capacity)	x	x	x	x	x	x	x
Mean Competitor RevPAR			x	x	x	x	x
Month Dummies		x		x	x	x	x
Month Dummies X Market Type				x	x	x	x
TripAdvisor/Priceline Average Rating					x	x	x
Short Term Ratings						x	x
Mean Chain Partner RevPar						x	x
Lagged Log(RevPar)							x
F-Stat	5.69	3.90	2.32	2.17	1.94	1.76	1.76
p-value	.017	.048	.127	.140	.163	.185	.185

Note: This table presents the results of the test for serial correlation from Wooldridge (2002). The p-value shown corresponds to the probability of falsely rejecting the null hypothesis of no serial correlation.

Table 11: Instrumental Variables Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged # Reviews	-0.0000080 (0.0001)			-0.00072* (0.0003)	0.000091 (0.0003)	0.0012*** (0.0002)	-0.0015** (0.0005)
Lagged # Reviews X Independent	0.0012*** (0.0003)			0.0033*** (0.0008)	0.0029*** (0.0004)	0.0026*** (0.0003)	0.00067 (0.0013)
Lagged TA # Reviews		0.00030 (0.0012)					
Lagged TA # Reviews X Independent		0.022* (0.0110)					
Lagged TA # Characters			-0.0000098 (0.0000)				
Lagged TA # Characters X Independent			0.00011* (0.0000)				
Chain Affiliated	0.069 (0.0564)	0.31* (0.1329)	0.79* (0.3666)	0.032 (0.0303)	0.036 (0.0313)	0.036 (0.0313)	0.037 (0.0313)
Independent Competitors	0.0010* (0.0004)	0.0020* (0.0008)	0.0067* (0.0027)	0.0016*** (0.0003)	0.0015*** (0.0003)	0.0014*** (0.0003)	0.0015*** (0.0003)
Chain Competitors	-0.00059 (0.0003)	0.0011*** (0.0003)	0.0010 (0.0006)	-0.00036 (0.0002)	-0.00040 (0.0002)	-0.00033 (0.0002)	-0.00045 (0.0002)
Age	-0.0065 (0.0035)	-0.044*** (0.0027)	-0.050*** (0.0070)	-0.0041 (0.0057)	-0.0020 (0.0058)	-0.0019 (0.0058)	-0.0038 (0.0055)
log(Capacity)	-1.07*** (0.0675)	-0.37*** (0.0518)	-0.53*** (0.1453)	-1.05*** (0.0403)	-1.03*** (0.0403)	-1.03*** (0.0404)	-1.03*** (0.0403)
Mean of Competitor RevPar	0.0069*** (0.0003)	0.0062*** (0.0001)	0.0075*** (0.0003)	0.0066*** (0.0002)	0.0066*** (0.0002)	0.0066*** (0.0002)	0.0066*** (0.0002)
1 AAA Star	-0.0074* (0.0033)	0.73*** (0.1171)	0.29 (0.3388)	-0.0016 (0.0017)	-0.0021 (0.0017)	-0.0016 (0.0017)	-0.0020 (0.0017)
2 AAA Star	0.018*** (0.0017)	0.71*** (0.0806)	0.48* (0.2233)	0.024*** (0.0012)	0.023*** (0.0012)	0.024*** (0.0012)	0.024*** (0.0012)
3 AAA Star	0.049*** (0.0019)	0.64*** (0.0806)	0.39 (0.2267)	0.048*** (0.0013)	0.047*** (0.0014)	0.047*** (0.0014)	0.047*** (0.0014)
4 AAA Star	0.085*** (0.0038)	0.51 (0.3296)	0.21 (0.8912)	0.078*** (0.0033)	0.072*** (0.0033)	0.071*** (0.0033)	0.081*** (0.0038)
5 AAA Star	0.13*** (0.0099)	0 (.)	0 (.)	0.13*** (0.0089)	0.12*** (0.0091)	0.12*** (0.0092)	0.13*** (0.0092)
TripAdvisor Rating	0.013*** (0.0024)	-0.0034 (0.0058)	0.0057 (0.0156)	0.010*** (0.0024)	0.011*** (0.0025)	0.011*** (0.0025)	0.011*** (0.0025)
Priceline Rating	0.0063*** (0.0014)	0.0090 (0.0053)	0.036* (0.0163)	0.0061*** (0.0013)	0.0059*** (0.0013)	0.0061*** (0.0013)	0.0058*** (0.0013)
Mean of Last 5 on TA	-0.0069*** (0.0019)	0.012*** (0.0025)	0.015* (0.0064)	-0.0074*** (0.0019)	-0.0075*** (0.0019)	-0.0077*** (0.0019)	-0.0077*** (0.0019)
Mean of Last 5 on PL	-0.0048*** (0.0012)	-0.0042 (0.0032)	-0.020* (0.0099)	-0.0045*** (0.0012)	-0.0045*** (0.0012)	-0.0046*** (0.0012)	-0.0044*** (0.0012)
TripAdvisor Std Dev.	0.0036 (0.0042)	0.033*** (0.0053)	0.041** (0.0142)	0.0018 (0.0043)	0.0013 (0.0044)	0.0026 (0.0044)	0.000016 (0.0044)
Priceline Std Dev.	0.0036** (0.0014)	0.0093*** (0.0013)	0.0038 (0.0041)	0.0038** (0.0013)	0.0037** (0.0013)	0.0032* (0.0013)	0.0037** (0.0013)
Mean of Previous Month Ratings	-0.0017* (0.0007)	-0.0011 (0.0011)	-0.0022 (0.0029)	-0.0015* (0.0007)	-0.0015* (0.0007)	-0.0015* (0.0007)	-0.0015* (0.0007)
Lagged Log(RevPar)	-0.095*** (0.0020)	0.51*** (0.0038)	0.50*** (0.0087)	-0.080*** (0.0012)	-0.080*** (0.0012)	-0.080*** (0.0012)	-0.079*** (0.0012)
Topic 1 Proportion (Room)	0.33*** (0.0645)	-0.074 (0.0505)	-0.32* (0.1581)	0.030*** (0.0037)	0.031*** (0.0037)	0.031*** (0.0038)	0.030*** (0.0038)
Topic 2 Proportion (Service)	0.27*** (0.0645)	-0.029 (0.0161)	-0.078 (0.0451)	-0.0099*** (0.0027)	-0.010*** (0.0028)	-0.0095*** (0.0028)	-0.0098*** (0.0028)
Topic 3 Proportion (General)	0.32*** (0.0653)	0.070* (0.0297)	0.16 (0.0854)	0.020*** (0.0031)	0.020*** (0.0031)	0.021*** (0.0031)	0.019*** (0.0031)
Topic 4 Proportion (Location)	0.34*** (0.0647)	-0.20** (0.0788)	-0.55* (0.2314)	0.049*** (0.0088)	0.051*** (0.0089)	0.049*** (0.0090)	0.054*** (0.0090)
Topic 5 Proportion (Brand)	0.37*** (0.0646)	-0.47** (0.1560)	-1.35** (0.5225)	0.072*** (0.0092)	0.072*** (0.0092)	0.069*** (0.0093)	0.081*** (0.0095)
Topic 6 Proportion (Spanish)	0.35*** (0.0654)	-0.014 (0.0902)	-0.44 (0.2742)	0.063*** (0.0096)	0.064*** (0.0096)	0.064*** (0.0096)	0.063*** (0.0096)
Topic 1 High Rating Share (Room)	0.015*** (0.0018)	0.024*** (0.0070)	0.047* (0.0197)	0.013*** (0.0018)	0.013*** (0.0018)	0.013*** (0.0018)	0.013*** (0.0018)
Topic 2 High Rating Share (Service)	0.0043 (0.0022)	0.036* (0.0177)	0.12* (0.0561)	0.0054* (0.0022)	0.0050* (0.0023)	0.0050* (0.0023)	0.0050* (0.0023)

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Table 11 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Topic 3 High Rating Share (General)	0.0067**	0.0089	-0.039	0.0043	0.0041	0.0032	0.0058*
	(0.0024)	(0.0114)	(0.0359)	(0.0024)	(0.0024)	(0.0024)	(0.0025)
Topic 4 High Rating Share (Location)	0.019***	0.062*	0.19*	0.013***	0.011***	0.0072*	0.017***
	(0.0030)	(0.0262)	(0.0831)	(0.0030)	(0.0030)	(0.0030)	(0.0033)
Topic 5 High Rating Share (Brand)	0.020***	0.049	0.19*	0.016***	0.014***	0.011***	0.020***
	(0.0031)	(0.0289)	(0.0900)	(0.0032)	(0.0032)	(0.0032)	(0.0035)
Topic 6 High Rating Share (Spanish)	0.015***	0.030*	0.10*	0.011***	0.0096**	0.0070*	0.014***
	(0.0029)	(0.0137)	(0.0460)	(0.0029)	(0.0030)	(0.0030)	(0.0031)
Under Renovation	-0.0016	-0.12***	-0.27**	-0.0075	-0.013	-0.021*	0.0013
	(0.0101)	(0.0327)	(0.1003)	(0.0100)	(0.0101)	(0.0103)	(0.0106)
Recently Renovated	-0.0010	-0.064**	-0.17*	-0.00089	-0.0029	-0.0060	0.0022
	(0.0049)	(0.0227)	(0.0670)	(0.0050)	(0.0051)	(0.0052)	(0.0052)
Property FE	Y	Y	Y	Y	Y	Y	Y
Owner FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Observations	241418	137722	137722	241418	241418	241418	241418
R^2	0.268	0.807	0.807	0.268	0.268	0.268	0.268
First stage F-Stat		12.54	11.71	177.02	165.43	166.47	116.92

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents a set of robustness tests for the main parameter of interest, the marginal effect of lagged # of reviews on independent versus branded hotels. In every case the dependent variable is Log(RevPar). Column (1) contains the primary specification as a benchmark. Columns (2-3) use minimum review length policy changes for both number of reviews and number of characters. This column excludes observations before 2008 and after 2013. Column (4-6) uses the 6, 9, and 12 month lagged number of reviews as instruments. Column (7) uses the number of reviews posted between 6 and 12 months earlier.

B Appendix B

This Appendix presents robustness checks for the results in section 4. Equation 2 measures the aggregate revenue premium earned by chain firms, and relies on hotels that add or drop affiliation with national chains during the sample period. One concern is that observing revenues before and after a hotel joins or leaves a chain may not be valid because hotels that leave chains may be underperforming in terms of revenue and that those that join chains may be overperforming (in the opposite case, that chain leavers are overperformers, the arguments presented here are equally valid.)

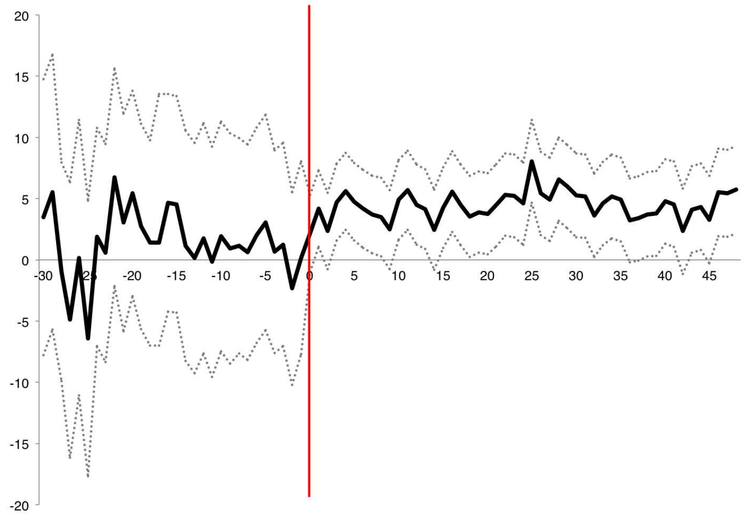
First, the nature of these switches is that they take place within already well-defined quality categories. In no cases does a firm that adds or drops chain affiliation see their AAA star rating change subsequently. These ratings correspond to basic physical amenities and offerings, such as breakfast being offered, presence of a pool, fitness center or conference facilities, as well as room layout and quality of construction. These elements are difficult and time-consuming to change and are not changing at the time of these switches, as evidenced by the lack of AAA rating changes in the data.

Second, more modest changes in quality that may precede or follow the addition or subtraction of chain affiliation are already controlled for using the TripAdvisor ratings, Priceline ratings, and the short term measures of each (the average of the 5 most recent ratings from both sites as well as the average of all ratings in the previous month.) If there are short term changes in things like service quality, on average these should capture that.

Third, while the estimates of the chain premium use the full data, measuring the full effect of the switch over many years while including property fixed effects, a more extreme version of the fixed effects argument can be used to insure this is not about reverse causality. In Table 12 below, I test for changes in revenue looking only at the quarter before and quarter after each switch occurred. This should, as much as possible, isolate the effects of the chain switch and remove longer term effects of changes in managerial quality or other factors. Column 2 compares the chain premium estimated using this very short time window to the estimates from the paper that use the full dataset and the results are not significantly different. While the data is too sparse to use this short-term window approach to measure the changes over time in the chain premium for different chain qualities, it is a useful robustness check to the methodology.

Fourth, an additional robustness check for concerns about reverse causation is to include leads or lags of the switch. If it is the case that national chains are dropping the underperforming hotels, and that the chain premium merely reflects this, than a one year lead of the switch should capture the difference in revenue and the variable measuring the actual switch should not be significant. Column 3 shows the results of this test. The one year lead is positive and significant, but the estimated chain premium falls only from 24.8% to 21.5%. A more comprehensive version of this exercise includes the full set of leads and lags and plots them. See Figure 13 below for the results of this test, which shows that the chain premium appears essentially immediately and in full at the time of the switch. If reverse causality in revenue drove the switch the effect would disappear under this specification or appear as a trend.

Figure 13: Chain Premium (in \$) Before and After Switching



Note: This figure shows detailed revenue estimates for firms that switch chain affiliation during the sample period. Dummies for the number of months before and after the switch occurred are included in revenue regressions and the coefficients on those are plotted. Month 0 corresponds to the first full month after adding affiliation. Dashed lines represent a 95% confidence interval.

Fifth, I find that 4.8% of hotels have a change in the number of rooms available or the owner/manager within one year of the switch taking place. These might pose the concern that major renovations are taking place roughly concurrent with the switch. In columns 5 and 7 of Table 12, I include only at the subsamples with and without these changes taking place. The results are very similar to the sample of switching hotels that maintain their current owner/manager and number of rooms.

On the whole, I believe these tests strongly suggest reverse causality is not driving the results on the chain premium, and that the chain premium measured in the revenue data and the steep fall over time in this premium for certain chain types are well measured.

Table 12: Chain Premium Robustness Tests

	(1) Full Sample	(2) 1 Qtr Window	(3) With Lead	(4) No Room Change	(5) Room Change	(6) Franchisee Change	(7) Same Franchisee
Chain Affiliated	0.248***	0.173***	0.215***	0.247***	0.256***	0.227***	0.251***
	(0.0311)	(0.0465)	(0.0302)	(0.0303)	(0.0447)	(0.0324)	(0.0325)
1 Year Lead Chain Switch			0.0732***				
			(0.0222)				
Independent Competitors	0.000249	0.00143	-0.000971***	-0.000671	0.00165*	0.00161**	-0.000569
	(0.000513)	(0.00635)	(0.000225)	(0.000604)	(0.000651)	(0.000598)	(0.000590)
Chain Competitors	-0.00118***	-0.365	-0.275***	-0.00110***	-0.00278***	-0.00238***	-0.00105***
	(0.000291)	(0.266)	(0.0555)	(0.000283)	(0.000672)	(0.000573)	(0.000278)
Age	0.0452	0.0365	0.0613	0.0237	0.00686	0.00860	0.0234
	(0.0361)	(0.0371)	(0.0569)	(0.0167)	(0.00692)	(0.00630)	(0.0180)
Log(Capacity)	-0.793***	-0.698**	-0.820***	-0.853***	-0.759***	-0.757***	-0.857***
	(0.0593)	(0.241)	(0.0581)	(0.0588)	(0.0713)	(0.0659)	(0.0588)
Mean Competitor RevPAR	0.0109***	0.0157***	0.0114***	0.0108***	0.00922***	0.00999***	0.0108***
	(0.000898)	(0.00280)	(0.00114)	(0.000958)	(0.00101)	(0.000810)	(0.000986)
TripAdvisor Rating	0.0133**	0.0314	0.0236***	0.00373	0.00143	0.00125	0.00413
	(0.00500)	(0.124)	(0.00560)	(0.00475)	(0.0156)	(0.0141)	(0.00469)
Priceline Rating	-0.00103	0.0941	-0.000397	-0.00174	-0.0110	-0.00978	-0.00221
	(0.00357)	(0.126)	(0.00495)	(0.00326)	(0.0115)	(0.0109)	(0.00321)
Mean - Last 5 on TA	0.00521	0.0911	-0.00572	0.00626	0.0229	0.0363*	0.00412
	(0.00408)	(0.117)	(0.00484)	(0.00378)	(0.0165)	(0.0146)	(0.00372)
Mean - Last 5 on PL	0.00532	-0.103	0.00311	0.00253	0.0167	0.0175	0.00296
	(0.00328)	(0.120)	(0.00471)	(0.00297)	(0.0112)	(0.0106)	(0.00291)
Previous Month Rating	-0.00162	-0.0494	-0.00340	-0.000492	-0.00592	-0.00522	-0.000163
	(0.00175)	(0.0342)	(0.00178)	(0.00163)	(0.00846)	(0.00653)	(0.00161)
Lagged # Reviews		0.00120		0.000192***	0.0000821	0.0000812	0.000193***
		(0.00163)		(0.0000316)	(0.0000472)	(0.0000438)	(0.0000316)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Franchisee FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month X Market Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	723,805	1,319	598,473	596,579	61,348	94,562	563,365

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents a set of robustness tests on the measurement of the chain premium. In each case the dependent variable is Log(RevPar). Column (1) shows results from the full sample. Column (2) excludes all data not from firms that add/drop chain affiliation as well as all time periods outside the quarter before and quarter after the switch occurs. It also excludes the quarter during which the switch occurs. Column (3) includes a variable that is a one year lead of chain affiliation status. Column (4) excludes firms that have a change in number of rooms available within one year of adding/dropping chain affiliation. Column (5) only includes firms that change room number within one year of adding/dropping chain affiliation. Column (6) excludes firms that have a change in franchisee (as noted by their tax ID) within one year of adding/dropping chain affiliation. Column (7) only includes firms that have a change in franchisee (as noted by their tax ID) within one year of adding/dropping chain affiliation. AAA ratings are generally excluded because no AAA ratings change within one year before or after the year a switch occurs.