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Essays on Competition Under Asymmetric Information

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Essays on Competition Under Asymmetric Information

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Essays on Competition Under Asymmetric Information

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This dissertation presents research on issues of competition and market structure in economics, and in particular considers the role of of asymmetric information in firm competition. This includes asymmetric information among firms, between firms and regulators and between consumers and firms. In the course of this I adapt and expand on recently developed methods for solving, estimating and simulating dynamic models of firm behavior. Finally, this dissertation focuses attention on firms' motivations for and the consequences of horizontal expansion, both in the form of horizontal mergers in a differentiated goods market and in the form of horizontal chain affiliation.

This research proceeds in three steps. In Chapter 2 I explore and document consumers growing ability to use new online reputation mechanisms to both share their experiences with a wide variety of firms and gain information from other consumers' shared experiences. In Chapter 3 I present a theoretical model of horizontal mergers in a dynamic industry setting. I use this model to

answer a question that increasingly interests antitrust policymakers concerned with innovation: In a concentrated industry, does allowing rival firms to merge increase or decrease total investment? This model has two important features. First, the environment is fully dynamic, and second, I allow mergers to occur endogenously.

In Chapter 4, I combine many of the concepts from Chapters 2 and 3 into on piece of research to address the question: why do firms organize into chains? I use of combination of reduced form and structural dynamic methods to examine possible answers to this question in the context of the hotel industry. In particular, I take advantage of recent advances in estimating dynamic industry models to show that there is no evidence in favor of the traditional explanation for horizontal expansion, economies of scale or cost efficiencies. Instead, using a detailed examination of hotel revenue along with firm and market data, I show that chain firms have a substantial demand side advantage resulting from the fact that consumers frequently have little information on firm quality. In this industry, then, asymmetric information seems to not only matter for chain affiliation, it is the only factor that matters.

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Chapter 1

Introduction

This dissertation presents research on issues of competition and market structure in economics, and in particular considers the role of of asymmetric information in firm competition. This includes asymmetric information among firms, between firms and regulators and between consumers and firms. In the course of this I adapt and expand on recently developed methods for solving, estimating and simulating dynamic models of firm behavior. Almost all questions involving competition and market structure have important dynamic implications and without considering these we might frequently reach the wrong conclusions. Finally, this dissertation focuses particular attention on firms' motivations for and the consequences of horizontal expansion, both in the form of horizontal mergers in a differentiated goods market and in the form of horizontal chain affiliation.

In Chapter 2 I explore and document consumers growing ability to use new online reputation mechanisms to both share their experiences with a wide variety of firms and gain information from other consumers' shared experiences. These resources, such as Yelp.com and TripAdvisor.com, are having a potentially dramatic impact on the informational environment in which firms compete. Nowhere is this more true than in the hotel industry. Due to low repeat business, this is an industry that had been characterized by unusually low consumer information. Over the past decade, however, websites like TripAdvisor.com and Hotels.com have allowed consumers access to detailed reviews and ratings, with these ratings typically displayed at the point of sale. To the extent that these online reputation mechanisms matter for competition, we might expect to see it first in this industry. While I cannot at this time consider a causal relationship between online reviews and firm performance due to unobserved firm characteristics, in this chapter I do show several correlation results. Chain and high quality firms are more likely to be reviewed and to have high numbers of reviews, but being reviewed is not associated with higher revenue. Higher mean ratings are strongly associated with higher revenue, however, and rating standard deviation is strongly negatively correlated with revenue.

In Chapter 3 I present a theoretical model of horizontal mergers in a dynamic industry setting. I use this model to answer a question that increasingly interests antitrust policymakers concerned with innovation: In a concentrated industry, does allowing rival firms to merge increase or decrease total investment? This model has two important features. First, the environment is fully dynamic, every period each firm makes decisions about entry, exit, investment and mergers. Because the research question is inherently dynamic, considering entry and investment behaviors, only a dynamic industry model can be used to examine them. Second, I allow mergers to occur endogenously, as opposed to examining the impact of exogenously conducted mergers as most of the prior literature does. Methodologically, solving this sort of model is very difficult, which is why very little prior research has included these elements.

Two opposing economic forces make this an interesting question. As large firms buy out smaller competitors, they improve their product quality, and thus might use mergers as a substitute for investment, lowering total investment in the industry. On the other hand, the windfall gain that comes from getting bought out creates a powerful incentive for new entry and for investment by small firms to make themselves an attractive merger partner. Ultimately, I find this second force typically outweighs the first and allowing mergers results in more investment and more innovation than restricting them. This model can eventually be used to solve for the optimal antitrust policy of a regulator with imperfect information on the state of the market and of the firms attempting to merge.

In Chapter 4, I combine many of the concepts from Chapters 2 and 3 into on piece of research to address the question: why do firms organize into chains? The spread of the horizontal chain model, where many firms operate under one banner and offer uniform goods or services, is well documented. I use of combination of reduced form and structural dynamic methods to examine possible answers to this question in the context of the hotel industry. In particular, I take advantage of recent advances in estimating dynamic industry models to show that there is no evidence in favor of the traditional explanation for horizontal expansion, economies of scale or cost efficiencies. Instead, using a detailed examination of hotel revenue along with firm and market data, including online reviews data, I show that chain firms have a substantial demand side advantage resulting from the fact that consumers frequently have little information on firm quality and value the quality signal a chain affiliation provides.

In particular, I show chains earn a revenue premium of over 20% and that this premium is consistent with the predictions of a model of low consumer information and not consistent with other potential explanations. This premium has also declined substantially over the years 2000-2012 as online reputation sites have proliferated, and disappears when only considering firms with a large number of online reviews. In addition, I solve and simulate a dynamic industry model using estimated profit parameters to consider the dynamic implications of policies that restrict the activities of chain firms. Along with being one of the first papers to estimate a dynamic model of firm competition with flexibly specified unobserved market level heterogeneity, this research presents and supports a new explanation for a large economic phenomenon, the spread of chains, that has attracted attention from economists and policymakers in a variety of fields.

This dissertation documents the changing nature of information available to consumers and explores expands on methods for fully considering the dynamic aspects of competition and market structure issues ranging from traditional horizontal mergers to estimating and simulating a model of horizontal chain affiliation.

Chapter 2

Online Reviews in the Hotel Industry

2.1 Introduction

Over the past decade, consumers have increasingly been able to share and document their experiences with a wide variety of firms. Other consumers have access to these reviews and ratings and can use them when making their own decisions. This spread of information has potentially dramatic implications on firm performance and conduct. In particular, it raises a number of questions of interest in economics and marketing. What impact do these reviews, their total number, average rating, variance of ratings, etc, have on firm profits? What firm characteristics are associated with generating different types of reviews?

The goal of this paper is to collect and document data on consumer reviews in the hotel industry and to answer these questions in that context. I combine data on hotel level revenue of all the hotels in the state of Texas from 2000-2012 with reviews data from TripAdvisor.com, the world's largest travel review site, as well as additional data on firm and market characteristics.

A number of previous studies have examined the topic of online reviews as they relate to product quality and firm performance. [44] forms a theoretical model of review variance and how it interacts with product quality and consumer tastes and then tests this model with critic review data and box office performance as well as Amazon book sales. In particular, they find that a high variance should and does increase revenue for low quality products and decrease it for high quality products.

[14] studies the impact of reviews on sales in the book industry by comparing sales on Amazon and Barnes and Noble, finding that that reviews impact sales, with negative reviews having a strong impact than positive reviews. [49] study video game data and find the effect of reviews on sales depends on both consumer and product characteristics, with larger effects for less popular games and more experienced users. [20] use a panel of data to test for causality between movie reviews and box office performance. They find reviews reflect unobserved quality differences and do not influence sales. Two papers, [25] and [18], use detailed data on user reviews for hotels and consumer behavior to discuss optimal rankings by travel sites.

2.2 Data

The state of Texas collects a special hotel occupancy tax. Consequently, the full quarterly revenues of all Texas lodging establishments is available from the Texas Comptroller of Public Accounts. Tax revenue data is particularly trustworthy because incorrectly reporting it is considered unlawful tax evasion. For each hotel I also collect location, capacity and a measure of age. This information, along with chain affiliation, was cross checked with a number of sources including the AAA Tourbook and various hotels booking websites. The AAA Tourbook also provides us with a standardized measure of quality, giving a rating of 1 through 4 stars for each hotel listed. Of the hotels in our sample, 57% of affiliated firms have been rated. As AAA does not rate firms below a minimum quality standard, unrated firms are assigned a score of 1 star. My analysis focuses on rural markets, in which the bulk of hotels are one or two stars. The full distribution of star ratings breaks down as follows: 52.9% one star or unrated, 28.9% two stars, 17.9% three stars, and 0.2% four stars.

I also collect data from TripAdvisor.com, the world's largest travel review website. TripAdvisor.com was until recently a subsidiary of Expedia.com, along with Hotels.com and Hotwire.com. Users rate firms on a 5 star scale and leave detailed reviews. The data is a December 2012 cross-section containing average user rating, the number and distribution of reviews, each firm's ranking within their market, and the number of reviews by reviewer type (business, family, etc.) I also calculate the standard deviation of user ratings from the ratings distribution.

The analysis here is largely restricted to rural markets, where a market is defined as rural if there is no other market within 20 miles of it.[1] This is for

[1]For all results that follow, I define market as nearest city but also include firms in the same county among potential competitors. In addition, because hotel customers are frequently highway travellers, there is still potential substitution across markets. As a result, for markets on major highways I test inclusion of the firms in adjacent counties as potential competitors. I find that including them has no significant effect on results.

several reasons. Large cities and their suburbs contain a very large number of hotels. These hotels are more horizontally differentiated in a number of unobservable ways, some cater to business travelers, others to recreational, and within a large, sprawling city such as Houston, location is a key concern. It is not necessarily clear, therefore, which firms are competing with whom, and thus how to define a market, and there is probably a large degree of unobserved heterogeneity. Fortunately, Texas contains a great many rural and isolated markets. After restricting attention to these markets, our sample contains 353 markets with 1465 hotels. The mean market had 2.22 chain and 2.77 independent hotels active in 2012.

Table 2.1: Market Summary Statistics

	Mean	Std Dev	Min	Max
County Firms				
Chains	4.24	3.76	0	19
Independents	4.15	3.41	0	17
Market Characteristics				
Daily Traffic	14,289	13,756	0	100,000
Population	20,130	279,734	880	423,970
Total Sales ($billion)	3.41	20.6	0.03	438
Gas Wells	326.6	737.3	0	6155
Oil Wells	461.9	843,5	0	8261
Unemployment	5.72	2.27	1.9	17.8

Note: This table presents summary statistics on market characteristics, where market refers to county.

To account for demand side factors that influence firm revenue and market structure, I collect a variety of data on each market. From the Census Bureau I collect data on county unemployment rate and population, and total county retail sales as measures of market size or business activity. From the Texas Railroad Commission I add data on the number of currently producing wells for both oil and natural gas in each county. I also gather Texas Department of Transportation data on average daily traffic passing through each market. This measure is a key determinant of demand in the rural roadside hotel industry. Summary statistics on these data can be seen in Table 4.1. Together, variation across time and markets in these factors should help capture exogenous shifts in demand. In particular, the growth of the natural gas industry in Texas over the past decade has had a significant impact on hotel demand and is clear exogenous to hotel performance.

2.3 Results

2.3.1 Number and Presence of Reviews

In this section, I summarize results on the number of reviews hotels receive on TripAdvisor.com. Reviews data comes from a 2012 cross-section. I consider the total number of reviews firms receive as well as the total by reviewer type and review type. First, I show results on the probability of being reviewed on TripAdvisor.com at all. Of $1,329$ firms active in 2012, only 817 have one or more review. There is no fee associated with gaining a listing on TripAdvisor but the individual firm must submit information including average prices. It is notable how many firms have no online presence on TripAdvisor, the world's largest travel information site. Table 2.3.1 shows the unconditional probabilities of being reviewed online. Chain affiliated firms are significantly more likely to be reviewed. This could be a result of higher demand, different customer base, or a chain policy of forming an online presence. Of the unreviewed firms, roughly 81% operate independently. In addition, roughly 78% of unreviewed hotels are 1 star hotels.

Table 2.2: Proportion of Firms with Online Presence

AAA Rating	$\star$	$\star\star$	$\star\star\star$
Chain	62.20%	82.64%	88.96%
Independent	34.02%	59.87%	71.65%

Table 2.3 shows a logistic regression on whether or not a firm has online reviews. Again we see chain firms are more likely to be reviewed. Conditional on chain affiliation or lack thereof, higher quality firms are more likely to have online reviews. Number of reviews is also positively correlated with being reviewed online. Among market characteristics, only traffic levels are positively associated with the likelihood of being reviewed, with county revenue being negatively correlated.

Table 2.4 shows results of a regression of number of reviews on firm and market characteristics, with and without market level fixed effects. Here, market is defined at the county level. A few results stand out. When market level factors are completely controlled for, we see chain firms have significantly

Table 2.3: Probability of Having Online Reviews

Firm Characteristics	
Chain	1.164***
	(0.211)
2 Stars	1.062***
	(0.212)
3 Stars	1.589***
	(0.270)
Age	0.0139
	(0.00875)
Log Capacity	1.192***
	(0.180)
Firm Characteristics	
Log County Revenue	-0.199*
	(0.0939)
Log Traffic	0.253**
	(0.0967)
Unemployment	-0.0430
	(0.0436)
Log Population	0.0121
	(0.115)
Log Gas Wells	-0.0110
	(0.0306)
Log Oil Wells	-0.0264
	(0.0298)
cons	-3.316*
	(1.301)
N	1329

Standard errors in parentheses

The dependent variable is one if a firm has a positive numbers of reviews.

Table 2.4: Number of Reviews

	(1) All Firms	(2) All Firms	(3) Reviewed Firms	(4) Reviewed Firms
Firm Characteristics				
Chain	3.157	4.750**	1.102	3.158
	(1.758)	(1.800)	(2.300)	(2.449)
2 Star	3.571*	2.431	0.826	-0.0803
	(1.772)	(1.802)	(2.354)	(2.467)
3 Star	11.30***	8.950***	6.624*	5.380
	(2.002)	(2.047)	(2.651)	(2.803)
4 Star	44.07***	267.0***	257.1***	263.1***
	(9.953)	(18.77)	(21.08)	(22.39)
Age	-0.0541	-0.214**	-0.297**	-0.411***
	(0.0686)	(0.0734)	(0.111)	(0.120)
Log Capacity	9.472***	7.673***	10.30***	6.863**
	(1.342)	(1.425)	(1.945)	(2.202)
Market Characteristics				
Log County Revenue	-1.562*		-2.342*	
	(0.705)		(1.029)	
Log Traffic	-0.773		-2.970**	
	(0.728)		(1.069)	
Unemployment	-1.025**		-1.405**	
	(0.327)		(0.479)	
Log Population	1.712*		3.120*	
	(0.861)		(1.247)	
Log Oil Wells	-0.911***		-1.404***	
	(0.217)		(0.296)	
Log Gas Wells	-0.491*		-0.929**	
	(0.222)		(0.307)	
Market Dummies	No	Yes	No	Yes
cons	5.090	-21.25***	41.72**	-7.851
	(9.823)	(5.398)	(14.43)	(8.750)
N	1333	1333	818	818
adj. R^2	0.210	0.086	0.282	0.032

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

more reviews than independent firm. In addition, higher quality firms, particularly 3 and 4 star firms have significantly more reviews. Notably, these results for 3 star and chain firms are no longer significant when only looking at reviewed firms. This implies their higher number of reviews is coming through the extensive margin and not the intensive margin. This is confirmed in Table 2.3.

We also see that older firms have slightly fewer reviews than new firms and having more rooms is associated with significantly more reviews. Surprisingly, while traffic is associated with a higher probability of being reviewed, among reviewed firms traffic is negatively correlated with number of reviews. Number of reviews is negatively correlated with the number of active gas wells, oil wells, and county revenue, as well as the unemployment rate in 2012.

2.3.2 Number of Reviews by Type

TripAdvisor.com requires users to specify the type of traveler they are when leaving a review. These categories are business, solo, couple or family. In Table 2.6 I present results on the number of reviews by reviewer type. A few points stand out. First, chain firms have significantly more reviews from business travelers as well as solo travelers. 3 Star hotels and larger hotels generate more reviews of each type, but these correlations are weakest for solo travelers. 4 Star hotels receive significant numbers of reviews from families and couples, but not solo or business travelers.

Unlike AAA ratings, which are formed using a standard criteria giving

Table 2.5: Average Number of Reviews per Firm by Market Type

Log Population	2.106***
	(0.542)
Log Traffic	1.295**
	(0.438)
Unemployment	-1.414***
	(0.208)
Log County Revenue	-1.587***
	(0.446)
Log Gas Wells	-0.161
	(0.139)
Log Oil Wells	-1.100***
	(0.140)
Water Adjacent	1.070
	(0.721)
Border Adjacent	0.497
	(1.403)
cons	25.30***
	(5.857)
N	1333
adj. R^2	0.098

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6: Number of Reviews by Reviewer Type

	(1) Business	(2) Family	(3) Solo	(4) Couple
Firm Characteristics				
Chain	1.222**	1.095	0.744***	0.100
	(0.384)	(0.618)	(0.167)	(0.567)
2 Star	0.632	0.943	0.388*	0.997
	(0.387)	(0.623)	(0.169)	(0.571)
3 Star	2.915***	3.809***	0.949***	2.363***
	(0.437)	(0.704)	(0.191)	(0.646)
4 Star	3.247	25.51***	-0.296	13.51***
	(2.174)	(3.498)	(0.947)	(3.209)
Age	-0.0189	-0.0272	0.00530	-0.0101
	(0.0150)	(0.0241)	(0.00653)	(0.0221)
Log Capacity	2.004***	2.648***	0.574***	2.467***
	(0.293)	(0.472)	(0.128)	(0.433)
Market Characteristics				
Log County Revenue	-0.150	-0.244	-0.0742	-0.563*
	(0.154)	(0.248)	(0.0672)	(0.227)
Log Traffic	-0.00146	-0.135	0.0956	-0.320
	(0.159)	(0.256)	(0.0693)	(0.235)
Unemployment	-0.0774	-0.292*	-0.0699*	-0.333**
	(0.0715)	(0.115)	(0.0312)	(0.106)
Log Population	0.217	0.408	0.00570	0.475
	(0.188)	(0.302)	(0.0819)	(0.278)
Log Gas Wells	-0.0444	-0.150	-0.0408	-0.170*
	(0.0485)	(0.0780)	(0.0211)	(0.0716)
Log Oil Wells	-0.00844	-0.235**	-0.0792***	-0.338***
	(0.0473)	(0.0761)	(0.0206)	(0.0699)
cons	-4.868*	-2.592	-0.285	6.520*
	(2.146)	(3.452)	(0.935)	(3.168)
N	1333	1333	1333	1333
adj. R^2	0.240	0.200	0.197	0.128

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

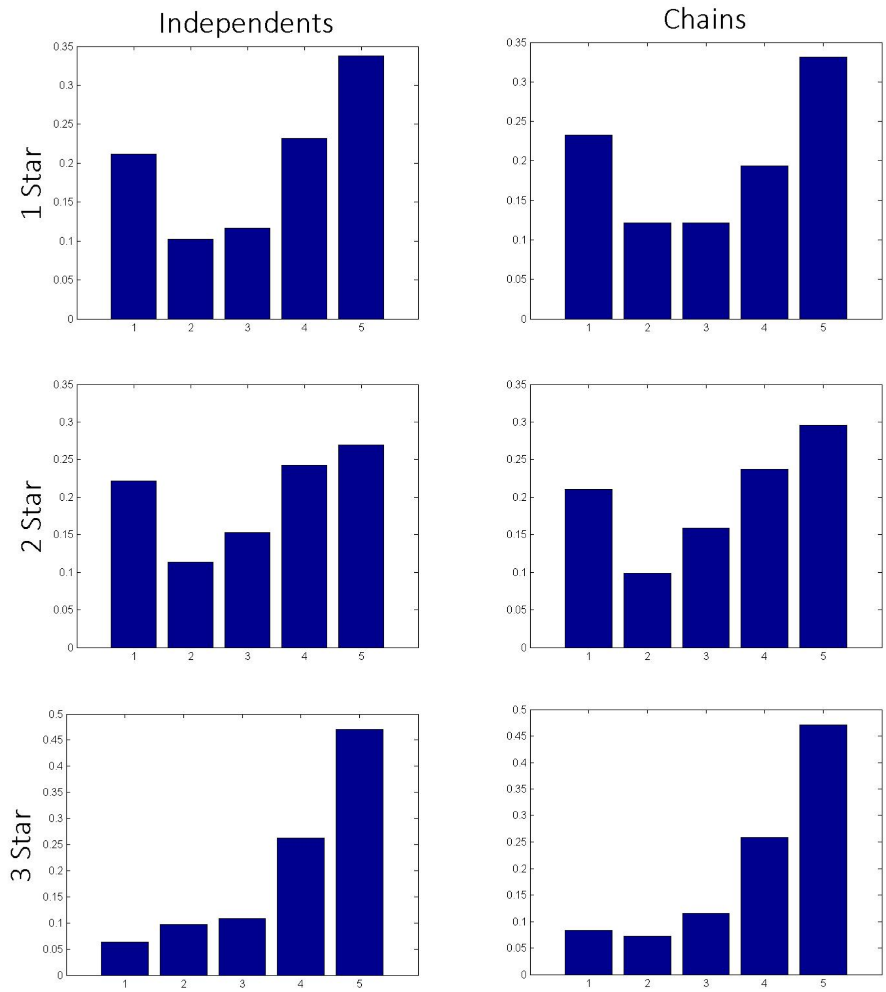
Table 2.7: Number of Ratings by Rating Type

	(1) 1 Stars	(2) 2 Stars	(3) 3 Stars	(4) 4 Stars	(5) 5 Stars
Firm Characteristics					
Chain	0.446	0.0836	0.374	0.724	1.546
	(0.259)	(0.185)	(0.220)	(0.422)	(1.183)
2 Star	0.780**	0.465*	0.878***	1.114**	0.331
	(0.261)	(0.186)	(0.222)	(0.426)	(1.193)
3 Star	-0.421	0.467*	1.005***	3.089***	7.160***
	(0.295)	(0.210)	(0.251)	(0.481)	(1.348)
4 Star	2.883*	7.439***	5.656***	12.15***	15.93*
	(1.467)	(1.045)	(1.247)	(2.391)	(6.699)
Age	0.0413***	0.0218**	0.0232**	-0.00484	-0.136**
	(0.0101)	(0.00721)	(0.00860)	(0.0165)	(0.0462)
Log Capacity	1.861***	1.162***	1.218***	1.955***	3.277***
	(0.198)	(0.141)	(0.168)	(0.322)	(0.903)
Market Characteristics					
Log County Revenue	-0.210*	-0.138	-0.133	-0.228	-0.855
	(0.104)	(0.0741)	(0.0884)	(0.169)	(0.475)
Log Traffic	-0.0774	-0.154*	-0.106	-0.0930	-0.347
	(0.107)	(0.0765)	(0.0912)	(0.175)	(0.490)
Unemployment	-0.155**	-0.114***	-0.166***	-0.236**	-0.352
	(0.0483)	(0.0344)	(0.0410)	(0.0787)	(0.220)
Log Population	0.299*	0.192*	0.0749	0.142	1.006
	(0.127)	(0.0904)	(0.108)	(0.207)	(0.579)
Log Gas Wells	-0.0995**	-0.0539*	-0.0645*	-0.144**	-0.131
	(0.0327)	(0.0233)	(0.0278)	(0.0533)	(0.149)
Log Oil Wells	0.0286	-0.0622**	-0.141***	-0.257***	-0.478**
	(0.0319)	(0.0228)	(0.0271)	(0.0520)	(0.146)
cons	-3.209*	-0.567	0.651	1.245	7.022
	(1.448)	(1.032)	(1.231)	(2.360)	(6.612)
N	1333	1333	1333	1333	1333
adj. R^2	0.140	0.161	0.189	0.217	0.139

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

them a close to objective measure of quality, online ratings are inherently subjective. Customers rate three and four star hotels differently than one star hotels based on their prior expectations about quality. Price paid and the customer's sense of "value" received also play a role. In addition, particularly positive and negative experiences are more likely to result in reviews, relative to average ones. Figure 4.5 shows the distribution of reviews by number of firms for each firm type, where a firm type is number of stars and whether it is affiliated with a chain or operates independently.

Figure 2.1: Distribution of Ratings by Firm Type



Note: This figure shows histograms of consumer ratings on TripAdvisor.com separated by firm type, where firm type is either chain or independent, and stars refer to AAA quality ratings.

In Table 2.7 I present results on the number of ratings received by hotels by rating type, on a 1 to 5 star scale. There is a general pattern linking quality as measured by AAA star ratings and TripAdvisor ratings. 2 star hotels are more likely than 1 star hotels to receive ratings of all types except 5 stars. 3 star hotels are more likely to receive high quality user ratings and less likely to receive low user ratings. Older hotels are more likely to receive low user ratings and less likely to receive high ones.

2.3.3 Mean Rating and Variance

In this section, I present correlations between firm and market characteristics, average firm-level online ratings and the standard deviations of these ratings. Results on average user ratings are presented in Table **??**. We see that chain firms are more likely to receive high user ratings, having roughly 11% higher ratings on average. Similarly, three star firms have 23% higher ratings than one star firms on average. Older firms and those with more rooms are more likely to receive low user ratings. The only market characteristic correlated with average rating is the number of oil wells, which is negatively associated with ratings.

I also consider correlations between firm and market characteristic and the average standard deviation of user ratings. Results are in Table **??**. The primary result is that firms with lower average ratings have lower standard deviations in their user ratings. After accounting for mean rating, the only significant predictor of rating variance is number of rooms, which is negatively

Table 2.8: Mean Online Rating

	(1) Log Mean Rating	(2) Log Mean Rating
Firm Characteristics		
Chain	0.108**	0.112**
	(3.12)	(2.85)
2 Stars	0.0453	0.0420
	(1.28)	(1.06)
3 Stars	0.208***	0.229***
	(5.22)	(5.10)
4 Stars	0.534	0.506
	(1.68)	(1.41)
Age	-0.0117***	-0.0112***
	(-7.01)	(-5.83)
Log Capacity	-0.0911**	-0.0791*
	(-3.11)	(-2.24)
Market Characteristics		
Log County Revenue	-0.0227	
	(-1.47)	
Log Traffic	-0.0221	
	(-1.38)	
Unemployment	0.00803	
	(1.11)	
Log Population	0.0247	
	(1.31)	
Log Gas Wells	0.00789	
	(1.71)	
Log Oil Wells	-0.0233***	
	(-5.24)	
cons	1.954***	1.444***
	(9.00)	(10.28)
N	818	818

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: Standard Deviation of Ratings

	(1)	(2)
Firm Characteristics		
type	-0.0576	-0.125
	(0.0579)	(0.0637)
2.rating	-0.00494	0.0386
	(0.0593)	(0.0635)
3.rating	-0.101	-0.000779
	(0.0688)	(0.0747)
4.rating	-0.829	-1.049
	(0.518)	(0.562)
age	0.00150	0.00499
	(0.00287)	(0.00317)
lcap	-0.253***	-0.224***
	(0.0491)	(0.0567)
urating	-0.293***	-0.291***
	(0.0228)	(0.0253)
Market Characteristics		
ls	0.0226	
	(0.0258)	
ltraf	0.0238	
	(0.0265)	
unemp	0.0333**	
	(0.0119)	
lpop	-0.0313	
	(0.0310)	
gaswells	0.0173*	
	(0.00762)	
oilwells	0.0155*	
	(0.00747)	
cons	0.146	0.700**
	(0.379)	(0.252)
N	790	790
adj. R^2	0.313	0.085

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

correlated with rating standard deviation.

2.4 Ratings and Revenue

In this section I examine the relationship between online ratings and firm revenue. As discussed above, a number of previous studies have found relationships between online ratings and sales in the book, movie and restaurant industries. Despite the prominence of user reviews at the point of sale in the travel industry, this issue has received less attention in this context.

Here I present correlations between the number of reviews, average rating, and other measures and individual hotel level performance. While firm revenues come from a panel the reviews data consist of a December 2012 cross-section. Therefore it is impossible to eliminate concerns about firm level unobserved heterogeneity. It could be the case, for instance, that a hotel has high user ratings and high revenues due to its high quantity not captured by the AAA star ratings and not due to a causal relationship between online rating and user demand.

The measure of performance I will focus on is daily revenue per available room, or "RevPar". This is the industry standard and is computed simply as total revenue divided by capacity and the number of days in the tax reporting period. I use the annual mean for 2012. Table 2.10 presents results of a set of regressions of firm average revpar on firm characteristics, including online ratings summaries. In column 1, I include a variable indicating whether or not a firm has reviews on TripAdvisor.com at all. Notably, having online reviews is not associated with higher revenue after controlling for other firm characteristics.

For each other column, I only use the set of reviewed firms. In column 2 we see a strong positive correlation between average user rating and revenue. Here a one star increase on TripAdvisor's five star scale is associated with a roughly \$6 per room per day increase in revenue, a roughly 30% gain.

In column 3, I include the standard deviation of user ratings. While controlling for mean rating we see a strong and large negative correlation

Table 2.10: Correlations Between Ratings and Firm Revenue

	(1)	(2)	(3)	(4)	(5)	(6)
type	5.331	8.212***	8.151***	9.113***	7.979***	7.983***
	(2.896)	(2.048)	(2.028)	(2.114)	(2.029)	(2.019)
2.rating	5.726*	4.521*	4.046*	5.378*	4.621*	4.228*
	(2.889)	(2.058)	(2.042)	(2.126)	(2.038)	(2.032)
3.rating	22.01***	15.55***	14.90***	19.16***	15.38***	14.91***
	(3.265)	(2.397)	(2.380)	(2.423)	(2.374)	(2.368)
4.rating	36.61	52.08**	49.39**	12.07	20.32	25.22
	(29.57)	(18.69)	(18.52)	(21.38)	(20.50)	(20.47)
age	-0.615***	-0.546***	-0.529***	-0.684***	-0.517***	-0.511***
	(0.116)	(0.103)	(0.102)	(0.104)	(0.102)	(0.102)
lcap	3.499	-2.898	-3.695*	-5.926**	-3.940*	-4.333*
	(2.306)	(1.846)	(1.841)	(1.913)	(1.851)	(1.847)
posrev	1.577					
	(2.420)					
urating		6.626***	6.019***		5.916***	5.598***
		(0.774)	(0.785)		(0.792)	(0.796)
revstd			-12.17***			-9.514**
			(3.367)			(3.490)
numreviews				0.189***	0.125***	0.0972**
				(0.0350)	(0.0346)	(0.0359)
_cons	18.81*	21.43**	31.07***	51.98***	25.52**	32.15***
	(8.585)	(8.044)	(8.399)	(7.546)	(8.046)	(8.365)
N	1333	818	818	818	818	818
adj. R^2	-0.031	0.320	0.333	0.273	0.333	0.340

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

between rating standard deviation and revenue. This suggests consumers may be averse to uncertainty when choosing a hotel, preferring a firm with all 3 star ratings to one with a mix of 1 and 5 star reviews.

Finally, number of reviews is positively correlated with revenue, even when controlling for mean and standard deviation of ratings, although this could simply reflect unobserved demand conditions.

Table 2.11: Review Summary Statistics by Chain

	(1) Number of Hotels	(1) Mean Reviews	(2) Reviews per Room	(3) Mean Rating	(4) Rating Std Dev.	(5) Business Share	(6) 5 Star Share	(7) 1 Star Share
Best Western	143	14.73	0.267	3.255	0.295	0.245	0.380	0.121
Holiday Inn Express	93	19.82	0.295	3.435	0.238	0.323	0.454	0.0774
Comfort Inn	56	18.96	0.312	3.589	0.261	0.290	0.483	0.0967
La Quinta	54	35.37	0.499	3.944	0.200	0.232	0.505	0.0863
Days Inn	52	14.27	0.269	2.375	0.285	0.222	0.218	0.345
Super 8	50	15.84	0.334	2.950	0.275	0.209	0.261	0.165
Hampton Inn	49	30.10	0.420	4.041	0.194	0.301	0.567	0.0472
America's Best Value Inn	35	8.886	0.200	2.443	0.364	0.244	0.286	0.325
Motel 6	28	10.93	0.169	2.732	0.373	0.170	0.167	0.321
Econolodge	21	9.238	0.171	2.190	0.274	0.247	0.209	0.303
Regency Inn	20	2.250	0.0811	0.875	0.134	0.171	0.258	0.392
Quality Inn	16	22.62	0.364	2.875	0.241	0.186	0.273	0.221
Ramada Inn	13	29.23	0.388	3.346	0.278	0.287	0.406	0.177

Table 2.12: Conditional Reviews Summaries by Chain

	(1)	(1)	(2)	(3)
	Hotels	Mean Reviews	Mean Rating	Rating Std Dev
Best Western	143	5.624	2.951	0.302
Holiday Inn Express	93	7.184	2.870	0.249
Comfort Inn	56	8.600	3.117	0.270
La Quinta	54	23.25	3.343	0.203
Days Inn	52	6.902	2.266	0.288
Super 8	50	10.05	2.896	0.277
Hampton Inn	49	16.84	3.417	0.201
America's Best Value Inn	35	3.643	2.519	0.379
Motel 6	28	4.256	3.198	0.422
Econolodge	21	3.258	2.077	0.278
Regency Inn	20	0.0525	1.157	0.174
Quality Inn	16	12.04	2.510	0.232
Ramada Inn	13	19.52	3.084	0.260

Chapter 3

Horizontal Mergers and Innovation in Concentrated Industries

3.1 Introduction

In a concentrated industry, does allowing rival firms to merge increase or decrease total investment? Antitrust authorities increasingly deal with industries, particularly in technological fields, characterized by high levels of investment and rapid changes in firm market share resulting from innovations produced by this investment. For these industries, the effects of a merger on dynamic considerations such as investment, entry and exit are large relative to standard considerations of price increases when determining the merger's likely effect on consumer welfare. Nevertheless, economic theory offers little guidance on the relationship between horizontal mergers and incentives to innovate. This reflects a number of challenges, both methodological and conceptual, which this paper works to overcome.

A merger between rival firms will affect their investment incentives in several ways. Investment typically imposes a negative externality on the industry, as some portion of the gains from a successful innovation come from stealing business from rival firms. By merging, firms will internalize this effect and reduce their investment accordingly. Firms may also buy out a smaller rival to acquire its new innovation, and so use the merger as a substitute for investing in the new technology itself. On the other hand, a merger may increase the new firm's ability to innovate by taking advantage of economies of scale or complementarities between the two firms' R&D departments. The prospect of being bought out may also encourage entry into the market by new firms, encouraging development of new products and technologies. If a firm buys out another and subsequently keeps both products on the market, the negative pricing externality between the two products is removed and the firm captures a larger share of the surplus generated by a successful innovation. Its not clear which of these effects will dominate without a model of mergers in a dynamic industry setting.

Simply observing whether investment increases or decreases post-merger in the data is potentially biased. The merger itself could be a response to some larger shock to technology, preferences or regulations that would cause firms or the entire industry to expand or contract in the absence of a merger. More generally, testing levels of investment post-merger empirically would typically rely on a test statistic that assumes independent observations, but a merger is not a random event. Mergers strongly cluster over time and industries, and both the decision to merge and the decision to invest have strong strategic components that depend on rivals' actions.

To clarify intuition, consider the wireless telecommunications industry. This is an industry characterized by high expenditures on investment, rapid innovation, and is dominated by a few large firms whose market share is volatile in response to these innovations. Another notable aspect is that smaller firms and new entrants are commonly bought out by the industry's larger incumbent firms. Consolidation through merger has been the dominant mode of industry evolution over the past decade and a half. A prime concern of antitrust authorities when reviewing these mergers has been the effects of the merger on firm incentives to invest in improving their network or expanding coverage of the latest technology.

This paper contributes to our understanding of the impact of mergers on investment by studying mergers in an Ericson-Pakes style dynamic oligopoly model. I choose this approach for two reasons. As Gowrisankaran (1999) argues at length, studying the implications of exogenous mergers or those in a static model suffers from a number of flaws. Dating back many decades, a number of authors have shown that adding a dynamic component can overturn standard results on mergers.[1] More importantly, however, the issue that this paper is concerned with is inherently dynamic. Future investment, exit, and entry, along with the potential for other future mergers, can have a dramatic effect on the welfare implications and profitability of today's potential merger, and without a dynamic model these aspects are unaccounted for.

Despite this, little work has been done on models of dynamic mergers. Cheong and Judd (1997) study mergers in a dynamic model where firms

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set price and quantity and adjust using inventories. They present numerical results showing that short-run increases in profits can make otherwise unprofitable mergers worthwhile. Chen (2009) studies a market of capacity constrained, homogenous product Bertrand competition with investment. This model is hand-calibrated and results in mergers that are typically profitable and welfare reducing. Both of these consider only exogenous mergers.

Only a few studies have been done of endogenous mergers in a dynamic context. Pesendorfer (2005) derives theoretical predictions from a Cournot model with entry, exit and mergers. He finds that the standard Cournot result is overturned if firms expect the possibility of mergers in the future, demonstrating the importance of both dynamics and endogeneity. [37] study optimal merger policy in a 2 firm model of dynamic, endogenous mergers and find that antitrust policy can have a significant beneficial impact on firm investment policy. Gowrisankaran (1999, 2004) studies the issue in a standard dynamic oligopoly model and in a dominant firm model. This paper will in some respects follow Gowrisanakaran (1999) and so I will describe it in detail.

Gowrisankaran (1999) considers an Ericson Pakes style model of dynamic oligopoly with capacity-constrained, constant marginal cost, homogenous goods producers. Firms enter, invest, merge, and/or exit in each period. The merger stage consists of a sequential bid model where, in each period the largest firm may buy out any smaller firm. If it does so, the process begins anew. If it does not, the second largest firm may buy out any smaller firm, and so on. The model is parameterized and solved and a range of numerical results and comparative statics are presented. Because firms only merge to increase market share, and no countervailing effect such as cost reduction is present, consumer welfare is always worsened by mergers. Similarly, investment always declines as firms internalize the investment externality. The impacts on total welfare are ambiguous. Gowrisankaran (1999) is impressive for overcoming the many technical challenges of solving a large dynamic oligopoly model with endogenous mergers and we hope to build on this.

The question of how a merger impacts incentives to innovate is closely related to the larger question of what is the relationship between the level of competition in an industry and the amount of investment or innovation in that industry? This is one of the most important questions in economics, as long run welfare is determined by the rate of technological growth and antitrust policymakers have a direct impact on the level of competition in many industries. A horizontal merger represents a direct decrease in competition and by studying pre and post-merger investment I hope to shed light on this larger question.

I proceed by embedding an endogenous merger stage game into an Ericson-Pakes style dynamic oligopoly model where firms produce differentiated goods and compete in prices. They engage in entry, exit, and invest in future product quality. In each period firms may enter merger negotiations with one another. At this time they draw a random "synergy" value, reflecting the complementarities between their products. If the firms merge, in the following period they will produce a new, higher-quality product reflecting the previous qualities and level of synergy. This model is solved using the stochastic algorithm method of Pakes-McGuire (2001).

This paper provides contributions in two ways. By extending and enriching the literature on dynamic, endogenous mergers it furthers our understanding on the causes and consequences of horizontal mergers. By testing the impact of horizontal mergers on investment, entry and exit it contributes to our understanding of the relationship between competition and innovation.

The model is solved numerically and shown to fit broad facts from aggregate mergers data quite well in many respects. Several types of counterfactuals are considered. Preliminary results confirm our intuition on the main forces at play. We observe that firms primarily use mergers as a substitute for innovation, buying out smaller firms and consequently reducing their investment. Yet despite this, total entry and investment are significantly higher when mergers are allowed. The potential of receiving a windfall profit by being bought out by a larger firm provides a powerful incentive to enter the market and to invest so as to make one's firm an attractive merger partner.

The rest of this paper will be organized as follows, section 2 describes the model, section 3 describes the nature of equilibrium and method of computation, and section 4 presents preliminary results.

3.2 Model

Industry dynamics are based on the standard Ericson-Pakes framework, which features an infinite horizon, discrete time set of firms who invest, enter, and exit endogenously. This model and its properties and many applications are reviewed at length in Doraszelski and Pakes (2006), and will be given a shorter treatment here with more emphasis on the model's novel elements, specifically the merger stage. In the model, a set of constant marginal cost firms produce heterogenous goods and compete in prices. The goods differ with respect to their qualities and firms can invest in future product quality using a stochastic R&D technology. Each period, firms are allowed to enter merger negotiations with any other firm following a random sequence. Firms will attempt to merge if the net gain to the acquiring firm is greater than the reservation value of the acquired firm. The merger is quality-increasing, in that the products may be combined into a new product. Here, for each rival firm, the offerer will draw some "synergy" value reflecting the degree to which their products can be integrated.

3.2.1 Incumbent Firms

At any given time there are $n \leq \overline{n}$ firms active in the market, each producing a good of quality ω_i. This quality can be thought of as a function over a bundle of characteristics. For instance, the quality of a wireless company's product is a function of its coverage network, the quality of the network, the quality and variety of handsets, etc. The set of firms' qualities will be referred to as $\Omega = \{\omega_1, ..., \omega_n\}$. This is public information and represents the state of the industry. This closely follows the quality ladder model of Pakes-McGuire (1994). Consumers preferences form a discrete choice model, with consumer k's utility from good i given by $u_{k,i} = g(\omega_i) - p_i + \epsilon_{k,i}$, where $g(\cdot)$ is an increasing and bounded function and $\epsilon_{i,k}$ represents consumers' differing tastes. Each consumer purchases one unit of the product which gives them the highest utility. They may also purchase an "outside option" whose utility is normalized to 0.

Following the work of McFadden (1974), if ϵ is drawn from an extreme value distribution, this results in the logit demand system:

$$q_i(p_1, ...p_n; \Omega) = M \frac{exp(g(\omega_i) - p_i)}{1 + \sum_j exp(g(\omega_j - p_j))} \tag{3.1}$$

where $q_i(\cdot)$ is firm i's demand and M is the size of the market, or the measure of consumers. Firms choose prices conditional on the set of goods in the market to maximize profits, computed as:

$$\pi(\omega_i, \omega_{-i}) = q_i(p_1, ..., p_n; \Omega)(p_i - c) \tag{3.2}$$

Firms invest in their future quality with a stochastic R&D type technology. Quality evolves according to:

$$\omega_{i,t+1} = \omega_{i,t} - \nu_{i,t} + \eta_t \tag{3.3}$$

The first component of this evolution is the outcome of the firms investment activity, where a firm chooses investment intensity $x_{i,t}$, and

$$Pr(\nu|x_i) = \begin{cases} \frac{\alpha x_i}{1+\alpha x_i} & \text{if } \nu = 1 \\ \frac{1}{1+\alpha x_i} & \text{if } \nu = 0 \end{cases} \tag{3.4}$$

where α parameterizes the efficiency of the investment technology. The remaining component of quality evolution is an industry wide shock η that takes the value 0 with probability δ and is 1 otherwise. This represents industry wide decline in product quality or improvement in the attractiveness of the outside option.

Firms also face a flat, fixed operating cost FC which must be paid each period. At the end of each period, firms choose whether to remain in business and pay FC or exit. The incumbent firm's end of period problem is thus:

$$V^I(\omega_i, \omega_{-i}) = \max\{0, \max_{x_i} -x_i + \beta EV(\omega_i', \omega_{-i}'|x_i)\} \tag{3.5}$$

3.2.2 Merger Stage

The bulk of previous research studying the implications of horizontal mergers has examined the behavior of exogenously merged firms. This is due to the fact that, although clearly superior in many ways, modeling endogenous mergers poses a challenge. In many industries there may exist a set of profitable but mutually exclusive merger arrangements. The mergers in this set represent multiple equilibria and there is no clear equilibrium selection mechanism. The simplest solution is to model non-cooperative mergers, where firms propose buyout offers according to some defined sequence which provides a unique equilibrium in each stage.

Gowrisankaran (1999) follows this approach, embedding in an Ericson-Pakes model a stage game wherein the largest firm acts first. It has the ability to propose a merger to any other firm. If it chooses not to the second largest firm may propose, and so on. The stage game employed here is similar although the sequence by which firms may propose mergers is the result of a random draw. While this adds to the difficulty of solving the model, it should result in a richer pattern of mergers.

At the beginning of each period, a firm will be randomly chosen and allowed to enter merger negotiations with any other firm. Two merger technologies will be considered. The first is quality improving. Before choosing its partner, the offering firm receives a random "synergy" value for each rival firm $\sigma_j \in [0,1] \forall j$. This represents the degree to which their products can be integrated into a new future product. The period following the merger, the new, combined firm will produce a product of quality $\omega_i + \sigma_j \omega_j$. For this, its helpful to think of a product more broadly than a single physical good, but rather as a bundle of characteristics or services. In wireless mergers, the network is expanded and the set of available handsets increases.[2] The degree of

[2]For instance, in attempting to purchase T-Mobile USA, in March 2011 AT&T claimed the following: "AT&T and T-Mobile USA customers will see service improvements - including improved voice quality - as a result of additional spectrum, increased cell tower density and broader network infrastructure. At closing, AT&T will immediately gain cell sites equivalent to what would have taken on average five years to build without the transaction, and double that in some markets. The combination will increase AT&Ts network density by approximately 30 percent in some of its most populated areas, while avoiding the need to construct additional cell towers."

synergy might reflect the amount of overlap between the two firms' networks pre-merger, for instance.

Under an alternative technology, the two firms' products will continue to be produced by the new combined firm. The combined firm will face different pricing incentives when competing in the product market. The firm will set prices to maximize the joint profit over all its products.

Conditional on the set of synergy draws (or lack thereof), the proposing firm will either propose a merger with the firm offering the highest return in the merger stage or pass on the option. If the firm passes, a new firm is chosen at random and given the opportunity to offer a merger. The process continues until all firms have had an opportunity or a merger occurs. The only restriction on mergers is a simple antitrust rule preventing merger to monopoly. Because firms know that if they refuse a buyout offer they may be the next firm with the power to propose a merger, they may have the incentive to turn down a profitable merger foreseeing another, more profitable merger with some other firm. Similarly, they may accept or propose a less valuable merger to prevent two other firms in the market from merging and becoming too powerful. Because synergy draws are random and private information, this merger stage game can be quite complex but results in a rich and fully endogenous pattern of mergers.

Once negotiations begin, the higher valued firm will always take the role of acquirer. The merger's surplus is the difference between the combined firm's value and the sum of the separate firms' values. If there is a positive surplus from the firms' merger, it will be split between the two parties. This split will be according to each firms bargaining power, which will be equal. The empirical finance literature has mixed results on the shares of a merger's surplus going to either party, but most work finds the shares roughly equal.[3] Endogenizing the bargaining powers is one aspect of ongoing work. The reservation price of the firm being acquired is its value if the negotiation fails and they move to the investment stage unmerged. The value to the acquiring firm is the difference in values between the combined firm and its value if negotiations fail. Let $V^B(\cdot)$ and $V^S(\cdot)$ be the values of the buyer and the seller, denote the purchase price of the acquired firm as

$$\tau_{ij} = V^S(\Omega'|m_{ij}=0)+\frac{1}{2}[V^B(\Omega'|m_{ij}=1,\sigma_j)-V^B(\Omega'|m_{ij}=0)-V^S(\Omega'|m_{ij}=0)] \tag{3.6}$$

where m_{ij} indicates whether or not a merger was agreed to by both parties, with 1 meaning it was. The first term is the reservation value of the acquired firm and the second term is the share of the surplus from the acquiring firm that is paid out.

The value of a firm at the beginning of a period is thus:

$$V(\omega_i,\omega_{-i}) = \pi(\omega_i,\omega_{-i}) - FC + \sum_i \sum_j \int_{[0,1]} Pr(m_{ij})V^I(\omega_i',\omega_{-i}'|m_{ij},\sigma_j)\mathrm{d}\sigma \tag{3.7}$$

[3]See, for instance, Ahern (2012).

where $Pr(m_{ij})$ is the probability of a merger between firms i and j, and includes the distribution over which firm is chosen to begin the merger stage and the likelihood of each pairing based on the synergy draws.

3.2.3 Potential Entrants

In each period, a single firm may enter the market. The potential entrant lives for a single period and must pay an entry cost to join the industry, becoming an incumbent and competing in the product market in the following period. Potential entrants draw a random setup cost from some distribution $F^e(\cdot)$ and compare this cost to the expected net present value of entering. The timing of the model is such that potential entrants make their entry and investment decision at the end of the period, simultaneous with existing firms making their exit and investment decisions. Thus entrants have the ability to observe any merger activity in the past period before entering. The entrant's potential value is given by:

$$V^E(\Omega, ce_i) = \max\{0, \max_{xe_i} -ce_i - xe_i + \beta EV(\omega_i', \omega_{-i}'|xe_i)\} \tag{3.8}$$

3.3 Equilibrium and Computation

I will consider Markov Perfect Equilibria (MPE) for this model. If $s \in \mathcal{S}$ represents some element of the state space, a MPE consists of:

- A subset $\mathcal{R} \subset \mathcal{S}$;

- Strategies χ^* for every $s \in \mathcal{R}$, where $\chi^* = (\chi^E, \chi^{EX}, m_{ij}, \tau_{ij}, x_i, xe_i)$ respectively governing entry, exit, mergers, buyout offers, and investment.
- Expected discounted values conditional on these strategies, $V^E(\Omega, ce_i), V(\omega_i, \omega_{-i})$, $V^M(\Omega, i, j, \sigma_j)\forall j$, and $V^I(\omega_i, \omega_{-i})$.

Such that:

1. The Markov process defined by any initial condition s_0 and the strategies χ^* has $\mathcal{R}$ as a recurrent class.
2. For every $s \in \mathcal{R}$, strategies are optimal given $V^E(\cdot)$, $V(\cdot)$, $V^M(\cdot)$, and $V^I(\cdot)$. That is, $\chi^*(\Omega)$ solves:

$$\max_{\chi^E} V^E(\Omega, ce_i), \max_{\chi^{EX}, x_i} V^I(\omega_i, \omega_{-i}), \max_{\chi^M, m_{ij}, \tau_{ij}} V^M(\Omega, i, j, \sigma_j)$$

3. Values are consistent on $\mathcal{R}$. For every Ω and Ω' which are components of $s \in \mathcal{R}$:

$$V(\omega_i, \omega_{-i}) = \pi(\omega_i, \omega_{-i}) - FC + \sum_i \sum_j \int_{[0,1]} Pr(m_{ij}) V^I(\omega_i', \omega_{-i}' | m_{ij}, \sigma_j) \mathrm{d}\sigma$$

$$V^I(\omega_i, \omega_{-i}) = \max\{0, \max_{x_i} -x_i + \beta EV(\omega_i', \omega_{-i}' | x_i)\}$$

$$V^E(\chi^{E*}, xe_i | \Omega, ce_i) = \max\{0, max_{xe_i} - ce_i - xe_i + \beta EV(\omega_i', \omega_{-i}' | xe_i)\}$$

An MPE for this model can be shown to exist following Doraszelski and Satterthwaite (2010). There is no way to rule out the possibility of multiple equilibria. The multiplicity problem poses a challenge for counterfactual policy analysis and so will be discussed at greater length below. For a fuller discussion of potential multiplicity, see Doraszelski and Pakes (2006). The model is too complex to allow an analytic solution, instead, it is solved computationally using the stochastic algorithm of Pakes-McGuire (2001). The computational burden of the model described is enormous. The size of the state space grows exponentially in the number of firms and potential good qualities, and for each state, the integral over potential future states required to calculate the expected discounted value of different actions involves probability distributions over the random sequence of merger proposers, synergy draws, exit and entry behavior, and the outcomes of investment. The computational burden of this high-dimensional integral and state space is the reason there has been little work done on this type of analysis to date.

The measure of product quality ω is mapped onto the integers $\{0, ..., 10\}$, and the profit function is bounded above such that the upper bound on quality, $\overline{\omega} = 10$ does not bind in equilibrium. The number of firms or products allowed in the market is limited by $\overline{n} = 4$ which does bind in equilibrium in some periods. The next version of this paper solves the model for $\overline{n} = 6$ and this should no longer be the case.

3.4 Results

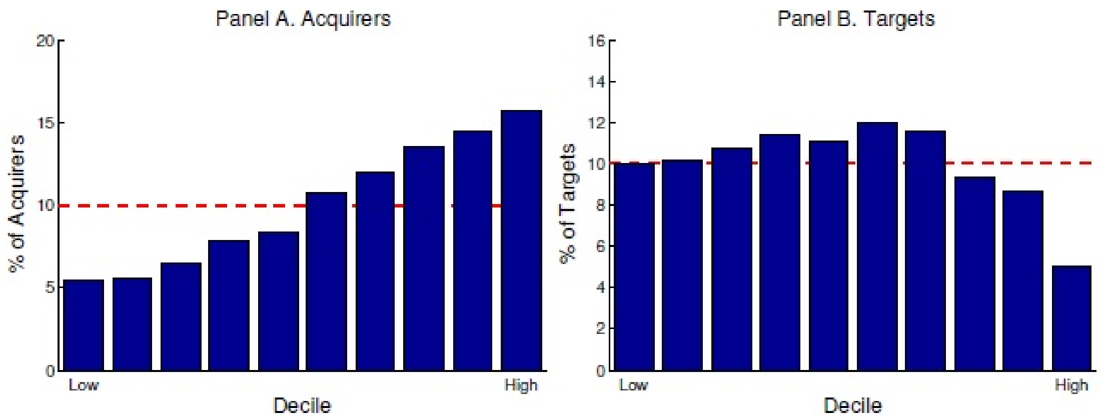
3.4.1 Model Performance

The model is solved numerically with initial parameter values taken primarily from Pakes-McGuire (1994) with merger fixed costs set low at .1. The full set of parameters can be seen in Table 3.1. The model produces results that fit the data quite well in several respects. Firm acquisitions occur in 4.3% of periods, compared to 3.89% in the Longitudinal Research Database over the period 1974-1992, as documented by David (2013). David (2013) also documents the pattern of firms acting as acquirers and targets in the Thomson Reuters SDC Platinum database. As Figure 3.1 illustrates, the share of acquirers is steadily increasing in firm size, whereas the distribution of targets over firm size is hump shaped and symmetric. The same pattern emerges endogenously in our results, as shown in Figure 3.2.

Table 3.1: Base Parameterization

α	3
β	.925
$\overline{n}$	4
$\overline{\omega}$	10
ω_e	1
FC	.1
c_M	1
δ	.6
ce	$\sim Unif[0, 10]$

Figure 3.1: Marginal Distribution of Merging Firms in Data



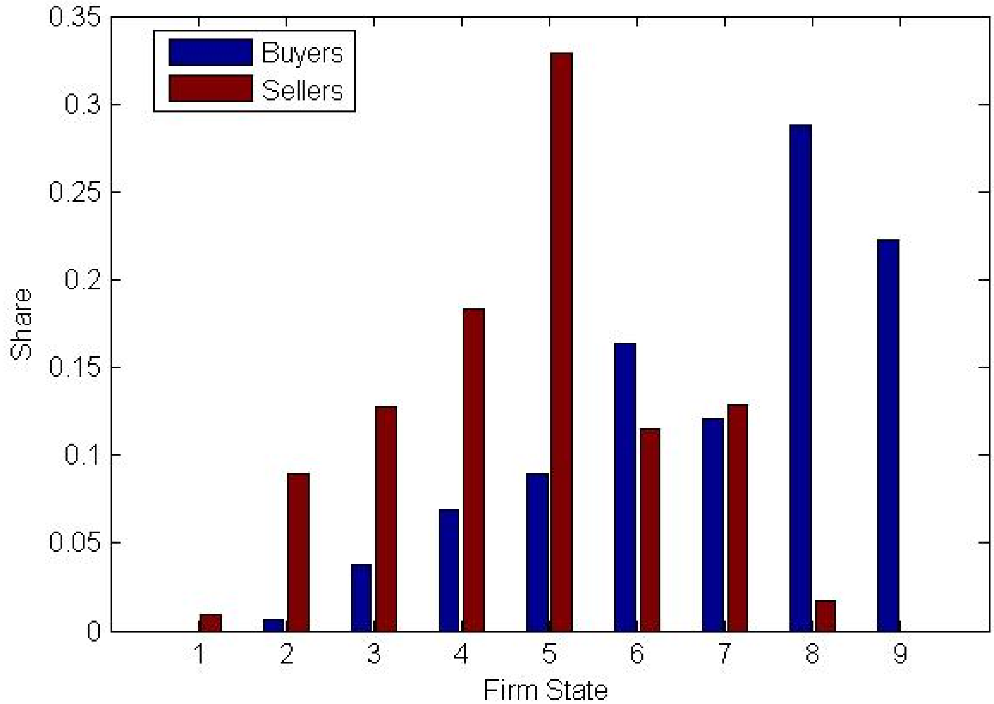
Note: This figure is taken from David (2013), it shows results from data taken from Reuters SDC Platinum database of transactions.

3.4.2 Mergers and Innovation Incentives

In this section I turn to the question of how horizontal mergers affect firm innovation. The general pattern in the model is of high investment by low and medium size firms trying to become the market leader, as very high profits are associated with having the highest quality good in the industry. Firms also invest significantly more in the presence of a "rival" firm, where rivals are defined as firms with quality states within 1 of one another. In a rivalry situation both firms invest significantly more in an attempt to escape it and become market leader. See Figure 3.3.

In addition to this, I consider the general relationship between investment and the level of competition in the market. Aghion et. al. (2005) identify an inverted-U relationship in this relationship, where market with low levels

Figure 3.2: Marginal Distribution of Merging Firms in Model



of product market competition as well as high levels experience lower levels of innovation. I plot investment levels in my model against market HHI and find the same result, see Figure 3.4.

To test the question of how horizontal mergers affect incentives to innovate, I first perform the simple comparison of the model with mergers to that without mergers. A brief note of caution is warranted at this point, as mentioned above the possibility of multiple equilibria cannot be ruled out for this type of model. I simply offer the standard disclaimer that as I worked to

Figure 3.3: Firm Investment Patterns

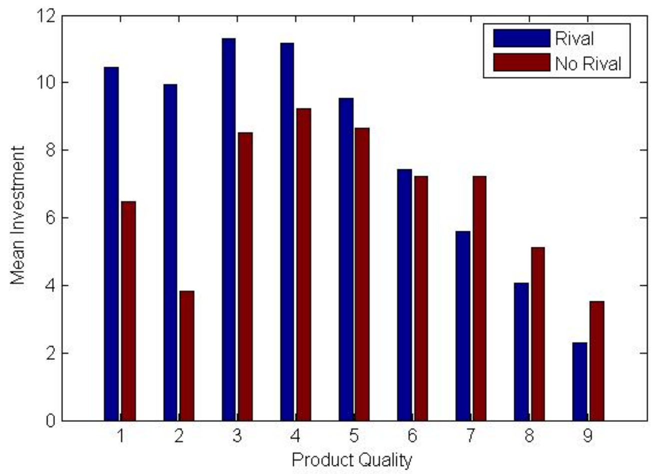
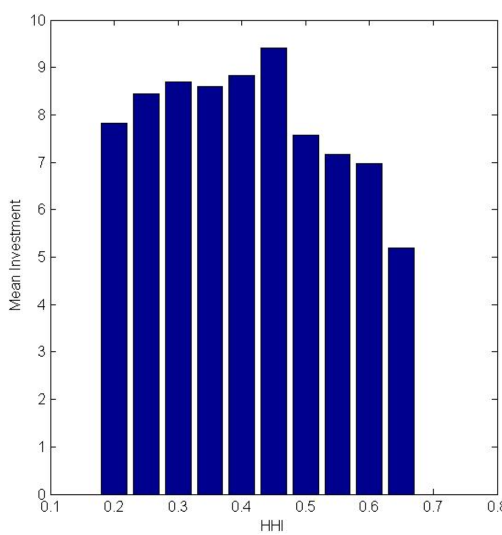


Figure 3.4: Inverse-U Relationship in Model



optimize the model's computation I experimented with a very large number of different initializations and updating procedures, no other equilibrium was reached than that presented here. Nevertheless, comparing two different solutions of the model may be invalid as some part of the difference in results could represent different equilibrium behaviors and not just the difference in policy or technology.

Table 3.2 shows results from this simple comparison. I show that when mergers are allowed the total amount of investment is significantly higher. This is true both of total investment and average firm investment. When mergers are allowed there is much more entry into the industry, resulting in more firms that are smaller on average and invest more. Entry increases from .1% of periods to 8.1% of periods. This follows our intuition that the prospect of being bought out and receiving a large windfall gain from the merger surplus increases the attractiveness of entry and spurs greater competition in that way. Because the smallest firms are rarely bought out, new entrants also have a high incentive to invest and improve their products until they are an attractive merger partner.

Table 3.2: Comparison of equilibrium with and without mergers

	Mergers	No mergers
Mean Investment	5.59	4.77
Mean Firm Size	6.57	7.66
Mean Number of Firms	3.45	2.99
Share of periods with entry	.081	.001
Share of periods with exit	.0029	.001

I now perform a more subtle counterfactual and one with no multiplicity concerns. I look at the results of the model with mergers and examine firm policy functions at states where mergers occur. At these states, a merger may or may not occur depending on random shocks over synergy and the sequence of offerers. For each I can examine firm policy functions post-merger and in a counterfactual where the merger does not occur and thus see the distribution of outcomes resulting from the mergers.

As table 3.3 shows, firms that merge invest significantly less than they would have in the absence of the merger. Large firms are using mergers as a substitute for investment. I also note that the other firms in the industry invest less post-merger than they otherwise would. This results from the fact that a majority of firms engaging in horizontal mergers do so to escape a "rivalry" situation, which results in less investment by the non-merging rival. When comparing the policy functions of potential entrants in the post-merger states to entry policies if no merger were to occur, we see a dramatically higher likelihood of entry post-merger. If no merger occurs the potential entrant will join the industry 39% of periods on average, but if there is a merger they will enter in 97% of periods.

I can also compare consumer surplus in the post-merger markets to those if the merger did not occur. Post-merger markets result in lower consumer surplus 58% of the time, as well as lower investment in 78% of periods, suggesting a role for active antitrust policy. One future goal of this paper is to more concretely identify which mergers result in lower consumer surplus and

Table 3.3: Comparison of policies at merger states

	Merger	No merger
Mean Investment	7.90	10.22
Mean Investment - Merging firms	5.80	10.40
Mean Investment - Non-merging firms	9.28	10.07
Likelihood of entry	.97	.39
Consumer Surplus	5.99	6.18

less investment in a way that can inform policymakers.

By comparing outcomes only at states where mergers occur, we do miss part of the full picture, specifically the behavior of firms that may be investing highly to position themselves as an attractive merger partner. The results of the two counterfactual exercises presented here complement one another in that respect, especially as they generally tell the same basic story. Firms buyout smaller firms as a substitute for investment but this process creates the incentives for higher total investment and greater entry.

3.5 Future Work

3.5.1 Multiproduct Firms

I also consider an alternative merger technology, where instead of combining products the newly merged firm continues to produce both products. Solving for equilibrium in an Ericson-Pakes model with multiproduct firms is computationally challenging and there is no previous literature considering this setting. Preliminary results for mergers in an industry with multiproduct firms are forthcoming, but suggest that the positive assortative matching observed in the data replicates in the model. That is, firms merge with similarly sized firms, as these mergers allow the largest reduction in the negative pricing externality that takes place in Bertrand competition.

3.5.2 Optimal Antitrust Policy

To this point the paper has only considered a trivial antitrust policy of not allowing mergers to monopoly, but it is possible optimal antitrust policy along two interesting dimensions. This requires inserting the antitrust authority into the game, specifying its objective function and information set, and solving for the optimal policy simultaneously with firm policy functions. This can take a number of forms and can answer a range of interesting questions concerning optimal policy under uncertainty. Several recent papers also look at the question of optimal antitrust policy in a dynamic setting. [37] studies the issue of optimal policy in a 2 firm homogenous goods market. They find that a policy of preventing most or even all mergers is welfare enhancing by preventing inefficient entry for buyout. [40] consider how antitrust policy might differ from a static policy if the setting is dynamic and rejecting a merger today influences the set of potential mergers in the future. They find that, when this effect is accounted for, it is optimal to reject some mergers which increase consumer surplus in order to induce more beneficial mergers in the future.

Here the antitrust authority's problem is defined by some information set s and some objective function $r(s)$. Each period a merger is proposed, the antitrust authority (AA) evaluates it against the discounted present value of this objective function by solving the problem

$$\chi^*(s, m) = \operatorname{argmax} q(s) + \beta \mathbb{E} V(s'). \tag{3.9}$$

Here, m is a vector describing the relevant factors of the merger

Chapter 4

The Spread of Horizontal Chains: Efficiency or Market Power?

4.1 Introduction

Over the past several decades, the chain business model has come to dominate most retail and service industries. [23] document a striking growth in shares of sales, employment and number of establishments affiliated with chains.[1] This trend has attracted interest from policymakers and economists concerned with issues ranging from employment and wages, to competition, to aggregate productivity.[2]. This broad scope reflects the fact that organizational form matters for a variety of economic outcomes. The success of the horizontal chain business model has been striking, but what explains this success? Why do firms organize into chains? The conventional explanation is that firms form chains to take advantage of economies of scale and operate more efficiently. An alternative, demand-side explanation is that consumers value chains' ability

[1] See Figure 4.1, taken from [23].

[2] Examples of work on wages and employment include [6] and [30] For work on competition, see [7], [9], and [31], among others. Research on aggregate productivity includes [23] and [12]. This is just a sample of the available literature, for a more comprehensive overview, see [32].

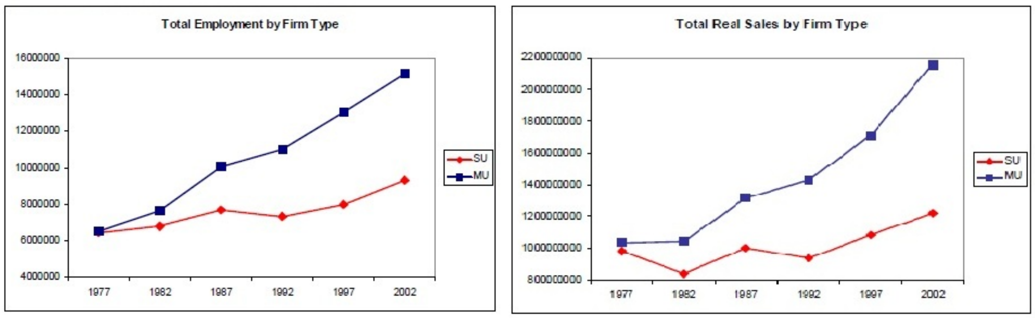
to credibly signal their quality in low information settings. These theories have different implications for welfare and for the future of competition in these industries. This paper seeks to examine these different explanations empirically and quantify the importance of them by studying the hotel industry in Texas.

Dating back to Adam Smith, economists have understood the role of scale economies in influencing the structure of industries. A natural explanation, then, for why independent businesses would join together into a chain network is that this allows them to exploit economies of scale to lower costs and enhance efficiency. The costs of advertising can be spread over more firms, inputs can be purchased with greater bargaining power and distributed using a network that spreads fixed costs. Firms may have greater access to capital when affiliated with a known and successful chain. Similarly, managerial expertise and other productivity and efficiency enhancing knowledge can be quickly disseminated.

A second major explanation arises from the pioneering work on the economics of information begun by Stigler, Akerlof, and Stiglitz, among others. In many industries, particularly industries with little repeat business or which sell experience goods, consumers have very prior little information on the quality of the product or service that firms offer. If consumers are risk averse, they favor firms whose reputation they know and may find search and experimentation costly.[3] Firms in settings where little information is available

[3]In a seminal article, [33] discusses the importance of firm reputation, [28] further exam-

Figure 4.1: The Spread of Chain Firms



Note: This figure is taken from Foster, Haltiwanger and Krizan (2006). Data comes from the Longitudinal Business Database. Here SU stands for single-unit and MU stands for multi-unit (chain).

may affiliate with one another and operate under one banner to take advantage of its reputation for consistent quality standards to attract risk averse consumers. Firms affiliated with a well-known chain can thus charge a substantial premium over independent firms offering uncertain quality even if the underlying product is identical. In essence, chains may be offering a solution to a lemons problem by facilitating repeat interactions that could not otherwise occur by providing uniform services in many settings. This is, in a way, economies of scale on the demand side, as the larger the chain is the more consumers have the opportunity to interact with it, increasing its value.

Which of these explanations is primarily responsible for the rise of the

ines the role of firm reputation in competition, and [13] explicitly model reputation building in low information environments as an incentive for horizontal expansion. Other examples of recent work on competition when consumers have low information and form brand loyalties include [10], [11] and [48].

chain model, lower costs or low information? The answer is of interest for several reasons. First, the implications for consumers may differ. Success due to greater efficiency or lower costs are unambiguously positive for consumers, improving competition and lowering prices. If the chain model is successful mainly due to low information, however, the effects are more ambiguous. Consumers may find themselves paying higher prices for the same quality good due to market power, but they may also find more high quality goods available.

Second, the answer has implications for competition in the future. Over the past decade online review and rating websites have allowed consumers to document and share their experiences with almost every conceivable type of firm.[4] Many industries are in the middle of a transition from a very low to relatively high information environment, and the path this transition will take depends on what has driven the chain model's success to this point. Finally, there are potentially antitrust implications. The extent of possible cost efficiencies is a key question when evaluating a merger. In addition, if chains can charge a premium because of their ability to facilitate repeat interactions, a merger of chains could increase this premium and thus increase prices. Theory alone cannot tell us which of these forces, efficiency or low information, is driving the success of chains. This paper instead will use a unique firm level dataset on the hotel industry to examine empirically the nature of chain affiliation and the relative contribution of each factor to firm

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

profits.

I use data on quarterly revenue for every hotel in Texas from 2000-2012. Two features of this data are particularly useful. I observe the full population of firms, allowing a direct comparison between chain affiliated and independent firms. In addition, observing firm revenue makes it possible to separate demand side factors from cost side factors. This data is supplemented with information from AAA and TripAdvisor.com, as well as information about the markets in which they operate. While the data is limited to one state, Texas is helpfully a very large and heterogenous state with interesting local demand shifters for hotel services. We observe data on 1,465 unique hotels competing in hundreds of distinct markets since 2000, with a close to even split between independent firms and chains.

The lodging industry is an ideal setting to examine the questions presented above for several reasons. First, hotels compete in a large number of geographically distinct markets. Second, unlike retailers or firms in other service industries, they offer close to a single product, a night's stay in a room. This product is differentiated between firms almost entirely on universally agreed on quality and not other factors. These result in a relatively straightforward problem with few confounding factors. Third, the trend towards chain firms in this industry closely matches the aggregate trend.[5] Finally, franchising and the hotel industry are significant sectors of the economy in their own right, with

[5]This can be seen by comparing Figures 4.1 and 4.7.

hotels generating \$177 billion in sales in 2007 and employing 2 million individuals according to the 2007 Economic Census, and franchises were responsible for \$1.3 trillion sales (9.2% of GDP) and 7.9 million employed ([32]).

The empirical strategy I pursue takes two parts. The first is a reduced form examination of hotel revenue and the value of chain affiliation. This includes examining the impact on revenues of hotels that add or drop affiliation during the sample period. I find that conditional on firm and market characteristics, chains earn over 20% higher revenue per room than independent firms. I then examine the nature of this advantage and find it to be consistent with a variety of predictions of a model of low consumer information as opposed to other potential explanations. The chain premium declines over the past decade as online reputation mechanisms become more widely used. The chain premium appears immediately when a firm joins a chain, as opposed to slowly phasing in, and it is positively correlated with chain size, as a model of repeat interactions would predict. Finally, online reviews data show strong correlations between customer information and independent firm success and for firms with large numbers of online reviews the chain premium disappears completely.

I next examine the conventional explanation that chain firms are more efficient than independent firms by examining their operating costs. These costs are unobserved, instead I estimate a dynamic model in the style of [3] to recover the cost structure of the different firm types to examine what cost or efficiency advantage is associated with chain affiliation. The identification strategy is to take observed revenues and observed entry and exit decisions and find the set of costs that best rationalize them. The dynamic model produces realistic estimates of firm operating costs. They suggest, however, that chain firms gain no cost advantage from their affiliation, and in fact may have slightly higher entry and operating costs than independent firms after controlling for quality and unobserved market level heterogeneity. This model can then be used to test the dynamic effects of policies limiting chain firms of the sort proposed in various jurisdictions.[6] I solve the model using the estimated parameters and run counterfactual simulations under a range of policies restricting chain entry. These suggest that limitations on chain firms result in fewer total firms in equilibrium and lower quality firms on average.

A growing literature addresses the spread of chains. In part this reflects the success of large retailers such as Wal-Mart ([6], [9], [23], [27] and [31]). This literature also takes advantage of newly developed methods to estimate structural models of competition from entry and location decisions, including [46], [47], and [1] on fast-food; [17] on movie theatres; [43] and [39] on video rental stores; and [38] and Villa-Boas (2007) on supermarkets; and [45] and [35] on hotels. These papers consider entry and location decisions, sometimes combined with structural demand models, and study their implications on firms' underlying cost structures and the nature of competition. [45] uses the same data source as this paper and similar methods in a study of land-use

[6]For instance, San Francisco bans firms with more than 11 outlets from operating in many areas. Other examples are discussed in section 4.

regulations.[7]

While these papers study various aspects of the economics of chain organization, none consider the broader question of why firms organize in this way. In addition, no previous work considers the demand side explanation for chain affiliation and how asymmetric information may be driving organization form patterns. My data allow this question to be addressed by including two features: data are not limited to location and entry decisions, but also include market outcome data in the form of firm level revenue, and the data also include the full population of firms in the market, and are not limited to specific chains like Wal-Mart.

[36] is one of the few studies that considers the same margin as this paper, the firm's decision of whether or not to join a chain. That paper also considers the hotel industry. Using a different dataset he examines how the decision to join a chain or not varies over different market types. He finds that firms are more likely to be chain affiliated on highly trafficked roads and less likely off major highways. He attributes this to potentially different shares of repeat business customers, where fewer repeat customers increase the importance of chain affiliation as a signal of quality. I find many of the same results in my data but am able to extend the analysis using a panel of firm revenue in addition to location decisions.

[7] [45] also estimates a dynamic model using Texas hotels data to test if land-use regulations raise firm costs. The key differences between [45] and this paper are that his focus is on total entry costs, which I do not estimate, and he restricts attention to the firms in the 6 largest chains.

Another literature in economics considers the firm's decision with respect to organizational form from a somewhat different perspective. In the vertical integration and franchising literature, these primarily take the form of cross-industry or cross-firm studies examining the correlation between organization form choice and potential explanations, including transaction costs, monitoring difficulty, property rights, and risk sharing. [32] or [34] and the papers described therein provide results on firm strategies with respect to what share of outlets to franchise, in what markets to franchise outlets, and on the relative performance of outlet type.

The rest of this paper will contain as follows: section 2 will describe the data and examine the revenue effects of chain affiliation, section 3 will develop a dynamic model and empirical strategy, and section 4 presents results from this model.

4.2 Revenue Analysis

In this section I will document a revenue premium associated with chain affiliation and argue that this premium is sufficient evidence of market power.[8] Ideally, we would observe prices and quantities directly, but unfortunately only overall revenue is observed and thus demand cannot be estimated, and in any event there is generally no single price for a hotel room. Prices vary over the time of year, day of week, and even method of purchase. I instead focus

[8] I use market power to mean the ability to raise prices above marginal cost, not in the stronger sense in which the term "market power" is used in antitrust settings.

on a firm revenue as a measure of performance,which is the measure most widely used in the industry. In a review of similarly rated hotels located in the same market, I observe that unaffiliated hotels almost never charge higher prices than comparable chain hotels. If chain prices are weakly higher than unaffiliated prices, higher revenue implies either prices are higher or greater capacity is filled despite similar prices. Both imply greater market power.

4.2.1 Data

The state of Texas collects a special hotel occupancy tax. Consequently, the full quarterly revenues of all Texas lodging establishments is available from the Texas Comptroller of Public Accounts. Tax revenue data is particularly trustworthy because incorrectly reporting it is considered unlawful tax evasion. For each hotel I also collect location, capacity and a measure of age. This information, along with chain affiliation, was cross checked with a number of sources including the AAA Tourbook and various hotels booking websites. The AAA Tourbook also provides us with a standardized measure of quality, giving a rating of 1 through 4 stars for each hotel listed. Of the hotels in our sample, 57% of affiliated firms have been rated. As AAA does not rate firms below a minimum quality standard, unrated firms are assigned a score of 1 star. My analysis focuses on rural markets, in which the bulk of hotels are one or two stars. The full distribution of star ratings breaks down as follows: 52.9% one star or unrated, 28.9% two stars, 17.9% three stars, and 0.2% four stars.

I also collect data from TripAdvisor.com, the world's largest travel review website. TripAdvisor.com was until recently a subsidiary of Expedia.com, along with Hotels.com and Hotwire.com. Users rate firms on a 5 star scale and leave detailed reviews. The data is a December 2012 cross-section containing average user rating, the number and distribution of reviews, each firm's ranking within their market, and the number of reviews by reviewer type (business, family, etc.) I also calculate the standard deviation of user ratings from the ratings distribution.

The analysis here is largely restricted to rural markets, where a market is defined as rural if there is no other market within 20 miles of it.[9][10] This is for three reasons. Large cities and their suburbs contain a very large number of hotels. These hotels are more horizontally differentiated in a number of unobservable ways, some cater to business travelers, others to recreational, and within a large, sprawling city such as Houston, location is a key concern. It is not necessarily clear, therefore, which firms are competing with whom, and thus how to define a market, and there is probably a large degree of unobserved heterogeneity. Second, hotel chains often own and operate a small number of their properties themselves. These are concentrated in large markets, whereas in rural markets nearly 100% of chain hotels are franchised out. This matters

[9]For all results that follow, I define market as nearest city but also include firms in the same county among potential competitors. In addition, because hotel customers are frequently highway travellers, there is still potential substitution across markets. As a result, for markets on major highways I test inclusion of the firms in adjacent counties as potential competitors. I find that including them has no significant effect on results.

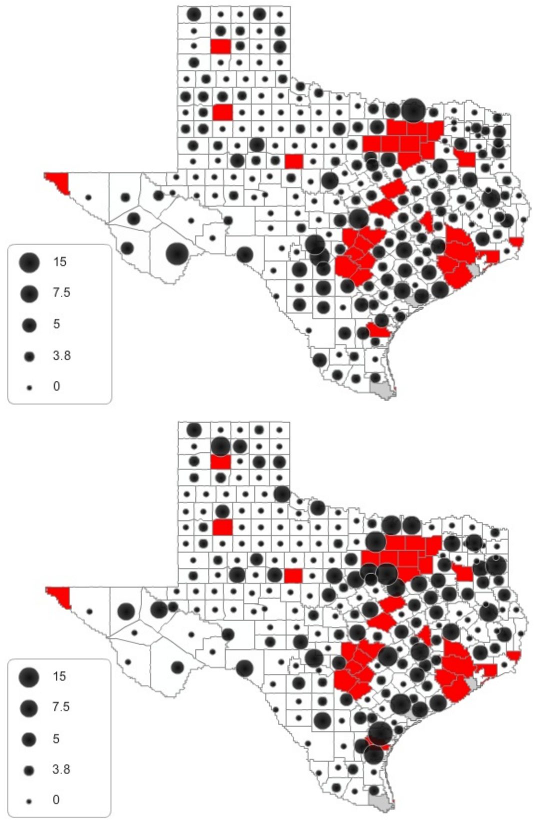
[10]Excluded markets are shown in Figure 4.8

because chain affiliation will be assumed to be endogenous at the level of the hotel for some of what follows. Fortunately, Texas contains a great many rural and isolated markets. After restricting attention to these markets, our sample contains 353 markets with 1465 hotels. The mean market had 2 chain and 2.77 independent hotels active in 2012. As seen in Figure 4.7, the Texas rural hotel industry displays the same dynamics seen nationally, very strong recent growth by chain firms.

The measure of performance I will focus on is daily revenue per available room, or "RevPar". This is computed simply as revenue divided by capacity and the number of days in the reporting period. For much of what follows I use annual means, aggregating up from quarterly, because of large seasonal fluctuations in demand and because most market data are annual. For the full sample, mean chain RevPar is \$32.07 and mean independent RevPar is \$19.07. Summary statistics can be seen in Table 4.2. The physical distribution of chain and independent firms is mapped in Figure 4.2, with excluded counties in red.

Data show that along with being more likely to have a high quality rating, chain affiliated hotels are more likely to be active in larger and more attractive markets. To account for demand side factors that influence firm revenue and market structure, I collect a variety of data on each market. From the Census Bureau I collect data on county unemployment rate and population, and total county retail sales as measures of market size or business activity. From the Texas Railroad Commission I add data on the number of currently

Figure 4.2: Independent and Chain Firms



producing wells for both oil and natural gas in each county. I also gather Texas Department of Transportation data on average daily traffic passing through each market. This measure is a key determinant of demand in the rural roadside hotel industry. Summary statistics on these data can be seen in Table 4.1. Together, variation across time and markets in these factors should help capture exogenous shifts in demand. In particular, the growth of the natural gas industry in Texas over the past decade has had a significant impact on hotel demand and is clear exogenous to hotel performance. Examples of this

Table 4.1: Market Summary Statistics

	Mean	Std Dev	Min	Max
County Firms				
Chains	4.24	3.76	0	19
Independents	4.15	3.41	0	17
Demand Shifters				
Daily Traffic	14,289	13,756	0	100,000
Population	20,130	279,734	880	423,970
Total Sales ($billion)	3.41	20.6	0.03	438
Gas Wells	326.6	737.3	0	6155
Oil Wells	461.9	843,5	0	8261
Unemployment	5.72	2.27	1.9	17.8

Note: This table presents summary statistics on market characteristics, where market refers to county. For visual representation, see Figure 4.9.

impact on revenue and entry patterns will be described below.

4.2.2 Revenue Estimates

In this section, I show that chain firms earn a substantial revenue premium over otherwise identical independent firms. Table 4.2 shows that, on average, chain firms earn higher revenues, but this could reflect a number of factors. To test if chain affiliated firms earn a revenue premium after controlling for a large set of firm and market characteristics, I regress RevPar on these market specific factors as well as the number of chain and independent competitors in the market. Specifically, I consider the model

$$RevPar_{imt} = x_{imt}\beta_1 + firm_{it}\beta_2 + c_{it}\delta^c + market_m + time_t + \epsilon_{imt}, \tag{4.1}$$

where x_{imt} are data on market characteristics such as population, as well as the number and type of competitors in each market, $firm_{it}$ are other firm characteristics such as AAA rating and TripAdvisor.com rating, c_{it} indicates whether a firm is a member of a chain in period t, and $market$ and $time$ are year and market dummies. 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.

While market structure variables are endogenous with respect to the same demand conditions that partially determine revenue, I am not concerned with this causing bias in estimation. Opening or closing a firm is a long term decision with new firms having a time to build of over a year. As a result, short term fluctuations in demand conditions should have little effect on market structure. I also include market fixed effects, so highly persistent unobserved demand conditions are accounted for. To control for medium term fluctuations, I include the aforementioned six demand shifters as wells as two variables measuring their rates of change.

With year dummies omitted for space, results are shown in Table 4.3. Because the dependent variable here is RevPar, coefficients can be interpreted as the effect on dollars per room per day.

After controlling for quality and other factors, we see that affiliating with a national chain is associated with an average premium of \$5.78 of daily RevPar. This represents a 27.7% premium, or roughly $\$120,000$ per year for a firm with 50 rooms.

This chain premium is the average over the 11 years in the sample. We can also look at how the revenue premium varies from year to year by interacting chain with year dummies. If the chain premium results from market power derived from low information, one might expect to see it decline over the past decade as information available to consumers online has improved.[11] The results can be seen in Figure 4.3. The chain revenue premium, expressed as a percentage, steadily decreases over the decade, from around 30% in 2002 to about 15% in 2010.[12] This decrease suggests the advantage to operating as a chain is fading, and potentially is evidence that online reputation mechanisms that have developed over the past decade are part of the reason why.

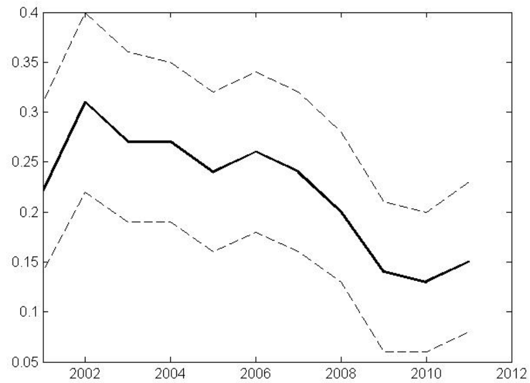
4.2.3 Switchers

There is an important potential sources of bias in the above analysis. Chain affiliation may be correlated with unobserved factors that increase revenue. This would be true, for instance, if chain hotels were more likely to be

[11]For background on the impact of search costs and consumer information on firm behavior and outcomes, see [8].

[12]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.

Figure 4.3: Chain Premium (%) Over Time



Note: this table presents the estimated chain premium as a % of total revenue after controlling for firm and market characteristics. Dashed lines represent the 95% confidence interval.

built on the best locations. This would cause upward bias in the estimate of the chain premium.

Our concerns about bias in revenue estimates stem from the fact that chain and unaffiliated hotels may differ systematically in unobservable ways. Ideally we could measure the counterfactual revenues of the same hotels with and without a chain affiliation. While this is impossible, 104 hotels do add or drop chain affiliation in the sample period. Roughly twice as many hotels add a chain affiliation as drop it. Here, I measure the effect of this change on revenue in a firm fixed effects context. The econometric model for RevPar r_{it} that I consider is:

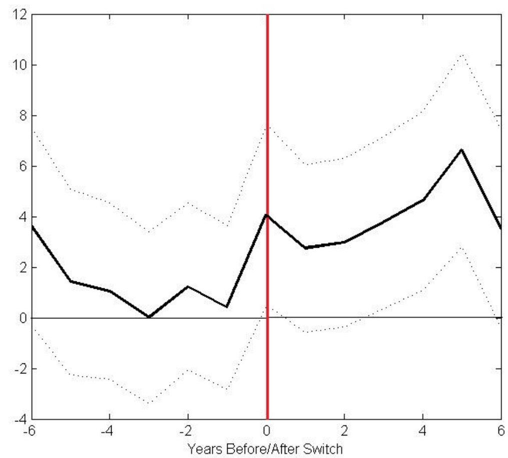
$$RevPar_{imt} = x_{imt}\beta_1 + firm_{it}\beta_2 + c_{it}\delta^c + market_m + time_t + a_i + \epsilon_{imt}, \quad (4.2)$$

where a_i is an unobserved, time-invariant determinant of revenue. Our concern is that a_i is correlated with c_{it}. Because we observe switchers, I can estimate a de-meaned version of equation 4.2 to eliminate a_i and estimate δ^c off the subpopulation of switchers. No firms that add or drop chain affiliation change their star rating, indicating that switches occur within fairly 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.

Results from this estimation are in column 3 of Table 4.3. Time constant explanatory variables are eliminated, and most estimates are similar to the previous results. The FE regression provides an estimate of the chain premium of \$4.35, lower than the estimate without firm fixed effects, but still a substantial advantage. This is equivalent to a 21.1% premium or roughly $\$95,000$ per year.

By adding dummies for the number of years before or after the switch occurred, we can trace out the timing of the revenue boost switchers receive and test whether the chain premium results from selection on a trend in unobservables. This would be the case, for instance, if chains were dropping underperforming firms or adding independent firms that had recently improved their quality. If this were the case, a one year lead of the switch should pick up this reverse effect and eliminate the estimated chain premium. I perform tests of this sort in Table 4.5. In column 4, we see the coefficient on a one year lead of joining a chain is positive but not statistically significant and when

Figure 4.4: Chain Premium Before and After Switching



Note: this table presents detailed revenue estimates for firms that add chain affiliation during the sample period. Dummies for the number of years before and after the switch occurred are included in revenue regressions and the coefficients on those are presented. Year 0 corresponds to the first full year after adding affiliation. Dashed lines represent a 95% confidence interval.

it is included the chain premium is $4.07 and highly significant. I show the full set of leads and lags visually in Figure 4.4. Two things stand out: first, there is no increase in revenue associated as firm approaches adding a chain affiliation, and thus the chain premium is not just a product of national chains selecting high quality firms to allow into their chain or vice versa. Second, the chain premium shows up at its mean level immediately, it does not need multiple years to phase in. This result is consistent with the chain premium being caused by consumer information. Under that explanation, as soon as the chain sign is raised, the advantage should go into effect.

4.2.4 Sources of Chain Advantage

The previous section has documented that chains earn a revenue premium of over 20% after controlling for firm and market characteristics, but can more be said about where this premium comes from? Theory suggests firms might use chain affiliation to gain market power by credibly signaling quality in low information settings. While it is impossible to observe how informed consumers are, this theory does suggest a variety of testable predictions.

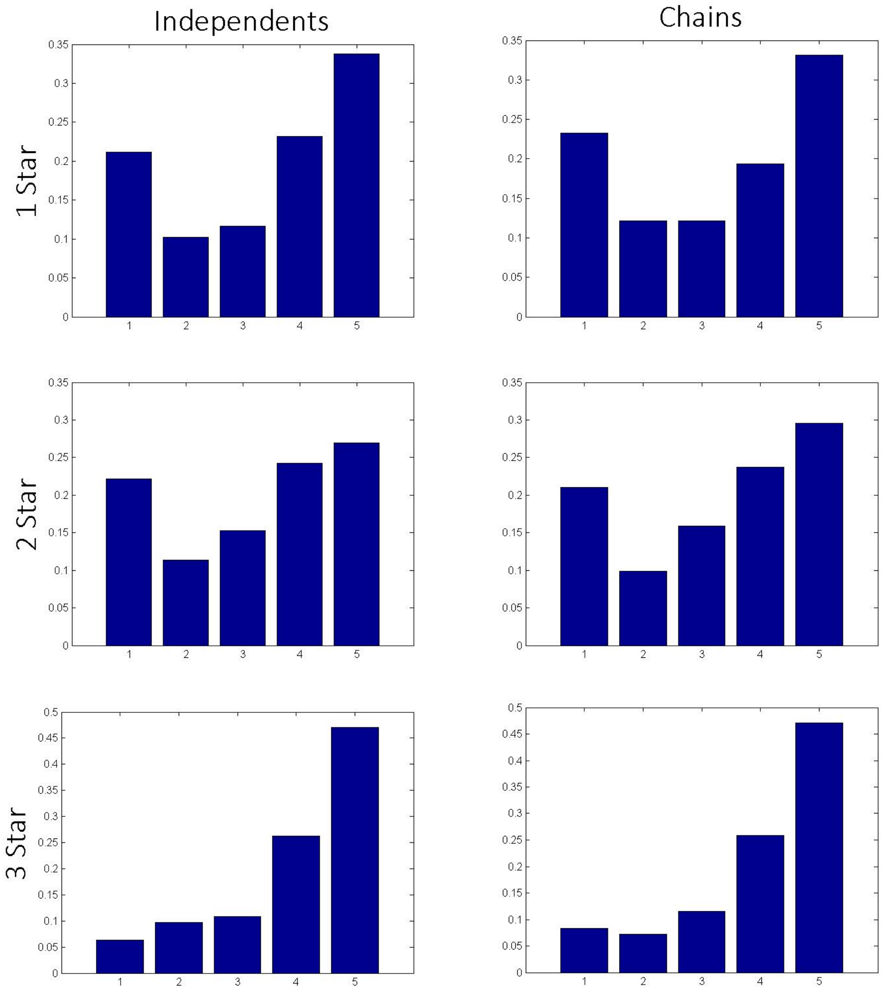
Two of these have already been discussed. If the chain premium results from poor information, it should be declining over time, particularly since 2005, as online reputation mechanisms have developed and become an important part of the hotel industry. This is indeed the case, as Figure 4.3 demonstrates, the chain premium is significantly lower at the end of the decade than at the beginning. This result is robust to specifications of the competitive environment and does not seem to be business cycle related. In Texas, during the recession in 2008 many regions were still booming and the same fall in the chain premium is seen in these areas as overall. If the chain premium were driven by use of loyalty programs, for instance, we would not see this fall, as loyalty programs have likely increased in importance during this period.

Additionally, if chain affiliation serves as a signal of quality, the chain premium should appear immediately when a previously unaffiliated firm joins a chain. Figure 4.4 shows that this is the case. If the premium were driven by subtle improvements in quality or management, we would expect it to take time to phase in. If the premium were just about the informational value of the name and sign it should appear immediately, as it does.

The next test relies on the theoretical underpinnings of the market power argument. Typically, consumers and firms overcome the problem of low information with reputations developed over repeated interactions. Chains may facilitate this process by operating firms in different markets with uniform standards of quality, increasing the potential for repeat interactions. The value of a chain's reputation should therefore depend on the number of potential interactions consumers can have with it. This prediction can be tested by interacting the chain premium with the number of outlets in that chain in Texas. The theory predicts a chain premium increasing in chain size. Results can be seen in Table 4.6. These estimates exclude independent firms. We see a strong, significant correlation between chain size and the chain premium. This lends support to the information based market power hypothesis of chain success.

I also consider this effect using firm level fixed effects. In this case I estimate the effect of chain size on firms that switch chains during the sample period. For these firms the effect is smaller but still significantly positive. There is a potential selection bias in both of these results, but nevertheless we see that firms switching to larger chains see an increase in their revenue. Next, I consider results from TripAdvisor.com customer reviews data. The number and consistency of online reviews can act as a measure of consumer information about different firms. While the number of reviews a firm receives is clearly endogenous, as it is a function of the firm's past history of demand shocks,

Figure 4.5: Distribution of Ratings by Firm Type



Note: This figure shows histograms of consumer ratings on TripAdvisor.com separated by firm type, where firm type is either chain or independent, and stars refer to AAA quality ratings.

the mean rating and standard deviation of ratings are valid measures. These data are inherently subjective, as consumers ratings may relate to their prior expectations, treating 4 star firms differently from 1 star firms, for instance. So long as they do not treat chain and independent firms differently, this does not present a problem for any of our results. Table 4.7 shows summary statistics on reviews, broken down by firm type and star rating.

There appear to be no systematic differences in mean rating, standard deviation, or number of reviews between chain and independent firms. In Table 4.5, we see the full distribution of ratings aggregated by firm type. Reviews are clearly not normally distributed, instead they are more likely to be drawn from the extremes, with a large number of 1 and 5 star ratings. While there are clear differences in the distributions between quality levels, within quality levels chain and independent firms have remarkably similar distributions of reviews. These results indicate that consumers do not systematically treat chain and independent firms differently when rating.

While I cannot measure the effect of number of reviews on revenue due to their endogeneity, we can still gain some information from them. I re-estimate the chain premium for the subset of firms for which the number of reviews is large. In Figure 4.6, I display the estimated chain premium for a range of cut-off points. Below this is the number of firms of each type included in the truncated sample. We see that as the number of reviews increases, the resulting chain premium drops almost exactly to zero. This suggests that as the amount of information available to consumers increases, the chain premium might disappear completely, although there is a potential selection effect here as well. The most visited and reviewed firms could have unobservable characteristics affecting this result. I test this by performing the same analysis but truncating on traffic and number of rooms and I do not find a similar pattern.

4.3 Recovering Costs

In this section I will describe the empirical strategy for recovering the cost structure of the industry. Why are we interested in these costs? I have already shown that organizing as a chain is associated with a significant revenue premium. This suggests that market power plays a role in the success of the chain model, but it does not give the full story. Whether chains also derive an efficiency or cost advantage from their affiliation matters for how we should think about them. If they do, and it is substantial, the implications for social welfare are different then if the only advantage derives from market power, and the implications for the future of the industry depends on whether chains will continue to thrive if the premium they are able to charge declines as consumers have access to greater information.

Unfortunately, these costs are not observable. Recovering them requires a structural model. Estimating this model serves another purpose, as well, in allowing for the counterfactual exercises used to consider policies restricting chain firms.

This methodology follows a recent tradition in empirical industrial organization of using two stage methods to recover the structural parameters of settings of firm competition that can be characterized as dynamic games, beginning with [2] and [4], extended more recently by [3]. These methods have recently been applied to a number of questions in industrial organization, including Environmental regulation ([42]), land use regulations ([45]), production spill-overs ([24]), demand fluctuations ([16]), repositioning costs ([38]), and dynamic effects of Medicare hospital regulations ([26]). A good recent overview of these methods is by [5].

The empirical strategy presented here begins with a model of the industry as a dynamic discrete game being played out across a number of local markets. Firms decide whether to remain active in the market or exit, and potential entrants must decide whether to enter or stay out, as well as what type of firm to open. Firms base their decision on the expected discounted stream of profits. By observing variation in their decisions across different types of firms and different types of markets, we learn the value of being active and how it varies over different states of the world. This value is the discounted stream of profits. By subtracting observable revenues from estimated profits, what remains are average per period operating costs. This approach essentially takes observed revenues and observed entry and exit decisions and finds the set of costs that best rationalize these two things. These are the costs we are concerned with when considering the proposition that chain affiliated firm's success is due to economies of scale in inputs, advertising, technology, etc.

4.3.1 Model

I model the hotel industry as a dynamic discrete game, where in each period firms compete against one another in local markets. The game is modeled following [22]. Each market contains a set of actors, differentiated along three dimensions: their quality type (1, 2, or 3 stars), whether or not they are affiliated with a chain, and whether they are an incumbent or a potential entrant.[13] Each firm in each period chooses whether or not to be active in the market and entrants determine their type.

Each market is described by a vector of state variables which determine payoffs. Denote the common state vector x_{it}. This includes endogenous variables, namely the number of each type of firm participating in the market. Denote the number of firms of each type as $\{n_q^c, n_q^u\}$ where $q \in \{1, 2, 3\}$. The endogenous component of x_{it} consists of a 6×1 vector containing n_q^c and n_q^u. The vector x_{it} also contains own type and market characteristics such as traffic levels.

In addition to this is, firms observe private information which they use in making their decision. Specifically, they observe a private signal about their profits in the coming year and use that signal in part when they decide whether or not to stay active. This signal can represent demand conditions,

[13]Because there is such a small number of 4 star firms, and none enter or exit during the sample period, I exclude them from this analysis.

cost conditions, or both. This is modelled as a vector of one period, IID shock to profits, defined as $\epsilon_{it}(a_{it})$, where firm actions are represented by a_{it}. For incumbents:

$$a_{it} = \begin{cases} 0 & \text{if exiting} \\ 1 & \text{if active} \end{cases} \tag{4.3}$$

For entrants:

$$a_{it} = \begin{cases} 0 & \text{if staying out} \\ (1,c,1) & \text{if entering as a 1 star chain} \\ (1,c,2) & \text{if entering as a 2 star chain} \\ (1,c,3) & \text{if entering as a 3 star chain} \\ (1,u,1) & \text{if entering as a 1 star unaffiliated} \\ (1,u,2) & \text{if entering as a 2 star unaffiliated} \\ (1,u,3) & \text{if entering as a 3 star unaffiliated} \end{cases} \tag{4.4}$$

Time is discrete over an infinite horizon, and the timing is as follows. At the beginning of each period, all active firms draw their private payoff values ϵ_{it} and decide whether or not to remain active in the market or exit irreversibly. At the same time, a set of potential entrants observe the state of the market x_{it} and a draw of private values ϵ_{it} and decide whether to enter the market or not. If they do not, they are replaced by a new set of potential entrants in the following period.

Once these decisions have been made, firms compete and earn revenues $R(x_{it}, a_{it}, a_{-i,t}; \theta_R)$ and incur operating costs $C(x_{it}, a_{it}; \theta_C)$.[14] The vec-

[14] I choose not to model the stage game that generates revenue, instead taking revenue as

tors (θ_C^c, θ_R) parameterize the cost and revenue functions. Note that while revenues depend on the actions of ones rivals, costs do not. The private information component of payoffs is additively separable. Per period payoffs can thus be written:

$$\pi(x_{it}, a_{it}, a_{-i,t}; \theta) = R(x_{it}, a_{it}, a_{-i,t}; \theta_R) - C(x_{it}, a_{it}; \theta_C) + \epsilon(a_{it}). \tag{4.5}$$

At the time of entry, potential entrants jointly decide whether or not to affiliate or remain independent, and which quality level to operate at. When entering, the firm pays an entry cost, $EC(c_i, q_i)$, that is a function of quality and affiliation. For potential entrants, private information shocks help determine not just whether the firm will be active but also what type and quality level they will choose.

Throughout this paper, all decisions are assumed to be made by local business owners. Despite operating under the brand of a national chain, that chain's headquarters makes neither the exit or entry decision. This is how the market operates in reality, with few exceptions. Hotels belonging to a chain must uphold certain quality standards and pay a share of revenues or flat franchise fee, but are otherwise independent.[15] This also keeps the game much

a flexible function of firm characteristics, market characteristics, and the number and type of competitors faced by each firm.

[15] In some cases, hotel chains do have centralized strategies with respect to entry, but the focus of these is on "showcase" hotels in large markets. In the rural markets I focus on here, the process is initiated and controlled by local entrepreneurs.

simpler than if a central body was making entry and exit decisions across a large number of markets.

4.3.2 Equilibrium

Following [22], firms' entry and exit strategies are restricted to be anonymous, symmetric, and Markovian. Firms thus only consider the current state vector of payoff relevant variables when making their decisions and all firms facing the same state behave the same way. Denote their strategies $\sigma_i : (x_i, \epsilon_i) \longrightarrow a_i$. Given these strategies, the incumbent firm's problem can be summarized:

$$\begin{aligned} V^I(x_i, \epsilon_i, \sigma_i; \theta) = \max_{a_i} \{ & \epsilon_i(a_i = 0), \epsilon_i(a_i = 1) + \\ & \mathbb{E}_{a_{-i}} \Big[\pi(x_i, a_i = 1, a_{-i}) + \beta \mathbb{E}_{x_i', \epsilon_i'} V^I(x_i', \epsilon_i', \sigma_i; \theta) \Big] \Big\} . \end{aligned} \tag{4.6}$$

The value of being an incumbent in state (x_i, ϵ_i) is either the value of exiting or continuing in the market, earning expected profits plus a continuation value, whichever is higher.

The choice of firm type is made is upon entry. Thus, entrants face a somewhat more complex problem. They make 3 decisions simultaneously, whether to enter, whether to operate as a chain or independently, and at what quality level. Let $q_i \in \{1, 2, 3\}$ denote quality level. The entrant's decision can be summarized:

$$
\begin{aligned}
V^E(x_i, \sigma_i, \epsilon_i; \theta) = \max_{a_i, [c,u], q_i} \{ & \epsilon_i(a_i = 0), \\
& -\theta_c^{EC}(q_i) + \epsilon_i(a_i, c, q_i) + \beta \mathbb{E}_{x_i'} V_c^I(x_i', \sigma_i; \theta^c), \\
& -\theta_u^{EC}(q_i) + \epsilon_i(a_i, u, q_i) + \beta \mathbb{E}_{x_i'} V_u^I(x_i', \sigma_i; \theta^u) \Big\} .
\end{aligned}
\tag{4.7}
$$

The value of being a potential entrant in state (x_i, ϵ_i) is the higher of the values of staying out or entering as a chain or unaffiliated firm of any quality level. Entering entails paying a cost that depends on type choice and then becoming an incumbent firm in the next period.

These firm value functions are indexed by the strategy functions $\sigma(x)$, which firms use to forecast their rivals' behavior and their own future behavior. The strategies $\sigma(x)$ form a Markov Perfect Nash Equilibrium if for all $V(\cdot)$ above and all possible alternatives $\tilde{\sigma}(x)$:

$$
V(x_i, \sigma(x), \epsilon_i) \geq V(x_i, \tilde{\sigma}(x), \epsilon_i). \tag{4.8}
$$

The presence of private information guarantees the existence of of at least one pure strategy MPNE, as shown by [19]. There is no way to guarantee uniqueness, however.

4.3.3 Empirical Strategy

In this section I discuss the variables and assumptions I will use to take the above model to the data. Until recently, estimating the underlying parameters of dynamic discrete games has been considered too difficult to be practical. The reason is that solving for an equilibrium of the game is computationally demanding and must be done for every set of parameters considered in solving a maximum likelihood problem. Beginning with [2] and [4], however, two step methods have been developed to avoid fully solving for equilibrium at every parametric evaluation. Instead, reduced form policy functions governing entry, exit and type choice are estimated directly from the data and are assumed to reflect equilibrium play. These are then used to estimate underlying structural parameters of the dynamic games.

The strategy followed here follows this tradition. Reduced form policy functions governing entry and exit are estimated and then these are used to estimate choice specific value functions directly. Re-solving the firm's discrete choice problem using estimated revenues and future values allows us to recover per period costs. In essence, I find the costs that best rationalize observed revenues with observed entry and exit decisions.

4.3.3.1 Revenue Adjustments:

Two adjustments must be made to observed revenues at this stage. First, I subtract franchise fees paid by chain affiliated firms. In the previous results on revenue, I do not for these fees. In that section I am primarily concerned with identifying and explaining a revenue premium earned by chain firms and am not interested in how this premium is divided between the franchisee and franchisor. In the current section I model the entry and exit decision of the franchisee and so it is necessary to remove these fees. Fortunately, hotel chains charge uniform fees across members and these are collected and published by Hotel Management, a trade publication. The standard contract consists of a flat initial fee ranging from $\$50,000$ to $\$100,000$ followed by $7-10\%$ of revenue thereafter. The fixed costs I estimate in this section are thus the net costs before fees, or the underlying economic costs of operation. I find that, on average, the chain revenue premium is split with around 50% going to the franchisee and 50% to the franchisor via fees.

Second, I adjust revenue for selection on entry and exit. We only observe the revenues of firms who do not exit and model the entry/exit process as a function of revenue shocks. Revenue thus needs to be adjusted for selection on these shocks. This can be done using a control function approach as described in [21]. Specifically, continuing to assume the private component of revenue is distributed according to a type 1 extreme value distribution, the expected value of this for active firms is

$$\mathbb{E}(\epsilon_i|x_i, a_i = 1) = \gamma - \ln(p(\widehat{a_i = 1}|x_i)). \tag{4.9}$$

After making these adjustments, revenues are estimated mostly as described in previous sections with two differences. First, for the purposes of our second stage estimation, revenues are only estimated over the state variables of the dynamic discrete game, *i.e.* no market dummies. Second, to keep the specification flexible, I include quadratic terms on market characteristics and interactions between firm and market characteristics.

4.3.3.2 Policy Functions:

The first step is estimation of firm policy functions determining entry and exit decisions. I assume the unobservable components ϵ_i are distributed according to a Type 1 Extreme Value (T1EV) distribution. Therefore, for incumbent firms, the choice probabilities thus take the logit form where:

$$p(a_i = 1|x_{it}) = \frac{\exp(x_{it}\beta)}{1 + \exp(x_{it}\beta))}. \tag{4.10}$$

[2] show that under certain conditions, this Conditional Choice Probability (CCP) is equivalent to the firm's policy function. For entrants, the problem is a bit more complex. Along with the entry decision, entrants are deciding whether to operate independently or not and which quality level to choose. Again I assume their shocks are distributed independently T1EV over these alternatives, resulting in a multinomial logit problem.

For both entrants and incumbents, the state x_{it} includes the full state of the market, ie $\{n^c_q, n^u_q\}\forall q$, as well as own type and market characteristics.

4.3.3.3 Value Function Inversion:

Here I describe how firm value functions are decomposed into revenue, cost and continuation values and how these continuation values are constructed using our estimates of policy functions. Because revenue is observable, once continuation values are estimated, it becomes straightforward to estimate the remaining piece, the firm's cost function.

First I give some notation. Denote the choice specific value function:

$$v(x_i, a_i) = \pi(x_i, a_i) + \beta \mathbb{E}_{x_i'} \overline{V}(x_i'), \tag{4.11}$$

where $\overline{V}(x_i)$ is the value of being in state x_i before realization of ϵ_i draws, which I will refer to as the ex ante value function. I find it by integrating $V(x_i, \epsilon_i)$ over the distribution of ϵ_i.

$$\overline{V} \equiv \int V(x_i, \epsilon_i) g(\epsilon_i) d\epsilon_i. \tag{4.12}$$

The model implies:

$$a_i^*(x_i, \epsilon_i) = \text{argmax}_{a_i} \{v(x_i, a_i) + \epsilon_i(a_i)\} \tag{4.13}$$

If I continue to assume ϵ_i is distributed T1EV, then the probability of remaining active is thus:

$$p(a_i = 1|x_{it}) = \frac{\exp(v(x_i, a_i))}{1 + \exp(v(x_i, a_i))}, \tag{4.14}$$

where the value of exit $v(x_i, 0)$ has been normalized to 0. [29], provided the insight that specifying the choice in this way can allows us to invert the above equation and write the choice specific value function as a function of estimable choice probabilities:

$$v(x_i, a_i) = \ln(p(a_i = 1|x_{it})) - \ln(p(a_i = 0|x_{it})). \tag{4.15}$$

Using our first stage estimates of $\widehat{p(a_i|x_{it})}$ from equation 4.10, I can thus form estimates of choice specific value functions directly off the data. I can also use our policy function estimates to calculate the conditional state transition function. Because private information shocks are assumed to be independent across firms, the probability distribution of a firm's rivals choosing a_{-it} is $P(a_{-i,t}|x_t) = \Pi_{j \neq i} p(a_{j,t}|x_t)$. Denote the transition of the state vector $F(x_i'|x_i, a_i, a_{-i})$. The transition kernel a firm thus faces is:

$$f(x_i'|x_i, a_i) = \sum_{a_{-i}} P(a_{-i}|x) F(x_i'|x_i, a_i, a_{-i}), \tag{4.16}$$

which can be calculated using our first stage policy function estimates and estimates of transition processes for exogenous state variables.

[3] show how, due to the T1EV assumption on ϵ_i, and due to the fact that exit is a terminal state, the ex ante value function can be expressed solely as a function of the CCP's. The intuition here is that, because the probability of exit is a function of the relative values of exit and remaining active, all information about the value of being active is contained in the probability of exit at this state. Specifically,

$$\int \overline{V}(x_i') f(x_i'|x_i, a_i) dx_i' = \gamma - \int \ln(p(0|x_i')) f(x_i'|x_i, a_i) dx_i', \tag{4.17}$$

where γ is Euler's Constant.[16] To simplify notation, I will refer to this item as:

[16]For a full derivation of this, see [3]

$$\widehat{\mathcal{V}(x_i, a_i)} \equiv \gamma - \int \ln(\widehat{p(0|x_i')}) f(x_i'|x_i, a_i) dx_i' \tag{4.18}$$

which I can estimate directly from our CCP estimates by simulating over the distribution $f(x_i'|x_i, a_i)$ a large number of times and calculating $\ln(p(0|x_i))$ at each draw. The choice specific value function in equation 4.11 can now be written as

$$v(x_i, a_i; \theta) = R(\widehat{x_i, a_i; \theta_R}) - C(x_i, a_i; \theta_C) + \beta \widehat{\mathcal{V}(x_i, a_i)} \tag{4.19}$$

The structural form of the discrete choice problem in equation 4.10 can now be solved, offset with estimates of $\widehat{R(\cdot)}$, and used to find the parameters of the cost function.[17] The firm's discrete choice is solved with fitted revenues in the current state and the expected one period ahead value. This approach has the appeal of being computationally straightforward, and thus can accommodate a large number of state variables which would otherwise pose a significant computational burden.

4.3.4 Unobserved Heterogeneity

The preceding assumes there is no persistent unobserved heterogeneity across firms or markets. The reduced form estimates presented earlier,

[17] Specifically, since a firm's choice probability is defined in equation 4.10, I re-solve a logit model on firm type and continuation value, offsetting revenue estimates. While parameter estimates in discrete choice models are typically scaled by the unknown T1EV dispersion parameter, because revenues are observed in dollars, costs parameters can also be expressed in dollars.

however, provide evidence of both market level and firm level unobservables influencing key revenue parameters. It is important, therefore, to allow for this when estimating our structural model.

In general, it is difficult to account for persistent unobservable effects in dynamic game models due to the highly non-linear nature of estimators. [2] show a method for accounting for permanent unobserved characteristics that influence payoffs in stationary dynamic games. [3] propose a method for estimating models with potentially time-varying unobservable factors that affect both payoffs and state transitions.[18] This is the approach I follow here.

I assume markets are in some unobserved state s, drawn from a discrete, finite support $\mathcal{S}$. This variable can affect firm profits, firm choice probabilities, and other state transition probabilities included in x_{it}, such as traffic or population. The algorithm iterates over two steps. In the first, the conditional probability of each observation being in each unobserved state is calculated using data and the assumptions of the model. In the second, these distributions are taken as given, and parameters governing payoffs and transitions are estimated conditional on them, treating them as weights.

In essence, in this procedure we are adding structure to what is unobserved by comparing what our model predicts with the outcome in the data. For example, if for market m, most firms in most periods earn revenues that are higher than their predicted value, and fewer firms exit than our model

[18] Previous applications include [9] on the dynamics of retail competition and [15] on worker productivity.

predicts, it indicates this market likely has a high value of the unobserved state.

These steps take place after finding reduced form estimates of policy functions and revenues, and before constructing continuation values and solving the structural discrete choice equation for cost parameters. I describe each step in detail below.

4.3.4.1 Expectation Step:

The first step is to take revenue and policy function estimates, and use them to estimate the distribution of unobserved heterogeneity in each market. Following [3], I refer to the first step the expectation step. After our initial reduced form estimates of revenue and conditional choice probabilities, we formulate the likelihood of observing revenues $\{r_{it} : i = 1, ..., N; t = 1, ..., T\}$ and actions $\{a_{it} : i = 1, ..., N; t = 1, ..., T\}$ conditional on our estimated revenue parameters β^R, policy function parameters β^a, and the assumptions of the model.

The goal is to find these likelihoods for all potential values of the unobserved state. To formalize this, denote the likelihood of observing firm i choose to be active in period t in market m with states (x_{imt}, s_m):

$$l_{it}(x_{imt}, s_m, \beta^a) = \frac{\exp([x_{imt}\, s_m]'\beta^a)}{1 + \exp(([x_{imt}\, s_m]'\beta^a)}. \tag{4.20}$$

Denote the likelihood of observing revenue r_{it} in the same state as:

$$\Omega(r_{it}|x_{it}, s_m, \beta^R). \tag{4.21}$$

Then the likelihood of the set of $\{r_{it}\}$ and $\{a_{it}\}$ in market m with state s is

$$\mathcal{L}_m(s_m = s) = \prod_{i \in m} \prod_t [\Omega(r_{it}|x_{it}, s_m, \beta^R) l_{it}(x_{imt}, s_m, \beta^a)]^{y_{it}} (1 - l_{it}(x_{imt}, s_m, \beta^a))^{1-y_{it}}. \tag{4.22}$$

Here $y_{it} = 1$ if the firm is active and is 0 otherwise. This expression represents the joint likelihood of all the observations from market m in the sample period, the revenues of each firm and each entry and exit decision, conditional on that market being in state s. After calculating this likelihood for each $s \in \mathcal{S}$, we can calculate the conditional probability of being in that state as

$$q^m(s) = \frac{\mathcal{L}(s_m = s)}{\sum_s \mathcal{L}_m(s_m = s)}, \tag{4.23}$$

which follows from Bayes' rule.

4.3.4.2 Maximization Step:

In the following step, the distribution of market level unobservables $q^m(s)$ is taken as given and a new set of parameters of policy and revenue functions are estimated using this distribution as weights. Here the unobserved state s is treated as observed. The likelihood function for revenue, treating unobserved states as observed, becomes:

$$\prod_i^N \prod_t^T \sum_s^{\mathcal{S}} q^m(s)\Omega(r_{it}|x_{it}, s, \beta^R), \tag{4.24}$$

where $\Omega(\cdot)$ represents the normal probability distribution function. The likelihood for incumbent firm policy functions is

$$\prod_i^N \prod_t^T \sum_s^{\mathcal{S}} q^m(s)pr(a_{it} = 1|x_{it}, s, \beta^a)^{y_{it}} pr(a_{it} = 0|x_{it}, s, \beta^a)^{1-y_{it}}, \tag{4.25}$$

where $pr(a_{it}|x_{it}, s, \beta^a)$ is specified as the logistic function. These likelihood functions are then maximized with respect to β^R and β^I respectively. These estimates are saved and the algorithm returns to the expectation step where they are used to update $q^m(s)$ using the previously described procedure. These two steps are iterated on until a fixed point in $(\beta^R, \beta^a, q^m(s))$ is found. At this point, the final stage estimation takes place, where cost function parameters are found by solving the structural discrete choice equation, now using $q^m(s)$ as weights. To briefly recap, the full structural estimation proceeds as follows:

1. Estimate initial revenue and policy function parameters (β_0^R, β_0^a) using flexible reduced form methods.

2. Generate initial distribution of unobserved states $q_m^1(s)$ using equation (4.23).

3. Using $q_1^m(s)$ as weights, estimate new revenue and policy function parameters (β_1^R, β_1^a).

- Repeat steps 2 and 3 k times, until $\beta_k^R = \beta_{k+1}^R$, $\beta_k^a = \beta_{k+1}^a$ and $q_k^m(s) = q_k^m(s)$.

4. Using the distribution of observables generated in the prior steps, estimate final stage structural parameters.

4.4 Results

In this section I present estimates of firm operating costs as well as estimates of entry and exit behavior. First, I discuss results assuming no unobserved heterogeneity at the firm or market level.

For incumbent firms, I estimate a logistic regression, where the dependent variable is whether or not the firm stays active, and the independent variables are market characteristics, firm characteristics, and interactions between them. Reduced form estimates of an incumbent firm's probability of remaining active are presented in Table 4.9. I test a variety of logit specifications as well as probit and poisson. We see that chains and higher quality firms are less likely to exit. Specification III, which includes quadratic and interaction terms, is used in what follows.

Entry is modelled as a flexible poisson process. Entrants of each firm type arrive at independent rates that vary with market characteristics. Results are shown in Table 4.10. While results differ across firm types, the two strongest predictors of entry for almost all firm types are natural gas production and interest rates. Markets whose existing firms are older on average also attract more entry.

I estimate county unemployment rate, total sales, and traffic as independent AR(1) processes. These transition probabilities are used along with firm policy functions to forward simulate and estimate continuation values at each state. Once continuation values are constructed, I form equation 4.19 for each firm. The unknowns in this equation are the parameters of $C(\cdot)$. I model $C(\cdot)$ as linear in firm type and market characteristics. These are estimated using logistic regression, where fitted values of revenues and continuation values are included. Results are presented in Table 4.11.

To correspond to our earlier measure of RevPar, costs are presented in terms of dollars per room per day. They are robust across policy function specifications.[19] Bootstrap standard errors appear below in parentheses[20]. As we expect, higher quality firms have correspondingly higher costs. Two star firms operating costs are $\$4-5$ higher per room per day than one star firms, and three star firms' costs are $\$13-14$ higher per room per day. Fixed costs per room are also decreasing slightly in number of rooms.

Most notably, chain firms have higher operating costs than independent firms, after conditioning on quality. This result is consistent across specification and is statistically significant in 2 of 3 specifications. The costs are

[19]See Table 4.12 which compares the resulting cost estimates using different first stage specifications of policy functions.

[20]These are determined by drawing whole market histories from the set of 353 markets, with replacement, and repeating the full procedure described above 100 times.

higher by $3 - 4$ per room per day. If larger chains are better able to achieve economies of scale, we would expect that operating in a larger chain would result in lower costs. Interacting chain status with dummies corresponding to chain size shows only weak evidence that operating in a larger chain lowers costs. Across many specifications, these results argue against the hypothesis that chains are successful because they are more efficient or productive than non-chain firms. To gauge the accuracy of these results, on average, I turn to industry survey data on costs. Smith Travel Research is an independent research firm that operates a large database on hotel industry data, producing annual reports on RevPar, gross operating profits and operating costs of hotel firms. Their annual Hotel Operating Statistics Study combines data from roughly 6,100 hotels in the United States. In Table 4.13, I present this summary data on average operating expenses for the limited service budget sector of hotels.

The average reported daily per room operating cost is \$31.00. For a 2-star chain firm, my estimates suggest an average daily cost of \$33.41, \$33.19, \$29.27, \$32.92, depending on specification. The operating costs I estimate thus fit very closely with average survey responses.

Results in the previous section show chain firms face slightly higher operating costs than similar independent firms, but these results do not account for unobserved heterogeneity. Its possible that chain firms locate in more attractive but more costly markets, or have higher unobserved quality, and that this quality is costly to achieve.

Final results with market heterogeneity accounted for are presented in Table 4.5. Results are for a $q_m(s)$ based on a uniformly spaced grid with 10 points. Increasing this number up to 100 was considered and showed little improvement. Total average costs do not change significantly, and still match up well with STR survey data, but we see that adding a market effect substantially changes the relative operating costs of chain and independent firms. Previous estimates suggested chain firms had operating costs higher by \$3.70 per room per day on average. This changes to \$.20 per room per day, implying chain and independent firms have no cost difference. This shows the important effects accounting for unobserved heterogeneity can have on key parameters.

The implication of this change is that chain firms operate in more attractive markets.[21] The decrease in the chain revenue premium when accounting for market heterogeneity was also evidence of this. The results on costs imply that locating in these markets results in higher costs, on average, and not chain affiliation. That the cost difference between chain and independent firms is so close to 0, however, suggests chains do not derive a significant cost advantage from their affiliation.

[21] This is confirmed by regressing the share of firms belonging to chains on market characteristics. This share is significantly higher in markets with higher traffic, business activity and oil and gas activity.

4.4.1 Counterfactuals

Since the advent of chain retailers in the early 1900's, their success and the effect on independent firms has been controversial and calls for policies to restrict their activities and "level the playing field" have been common. Today, policymakers in a variety of locations have implemented or are considering implementing restrictions on chain firms. The San Francisco, CA Planning Code bans or otherwise limits chain firms from operating in much of the city, and dozens of other U.S. cities have adopted similar measures. While they have done so for a variety of reasons which I do not attempt to address here, advocates for these policies almost universally cite worries that national chain firms are displacing local, independent firms. Having estimated a dynamic model, it becomes possible to examine this counterfactual directly.

The counterfactual question is what is the number of firms and distribution of firm qualities that would result if limitations on chain hotels in Texas had existed over the past decade? In simulating the distribution of firm types with limitations on chains, it is also possible to partially resolve the ambiguous effects of chain expansion on welfare. Since there is strong evidence that chains earn higher revenue after conditioning on firm characteristics, one might think they have a negative effect on consumers. But this chain premium is increasing in quality, and without the ability to signal quality that a chain affiliation provides, fewer firms might enter at higher quality levels. Our model allows us to simulate the distribution of firm quality without chains to test this.

Solving dynamic industry game models amounts to solving for a fixed point of a large system of non-linear equations. This is too complex to solve analytically and so must be done computationally. To do this I begin by forming firm profits for firm types in all market states using the estimated cost and revenue parameters discussed previously. I then solve for a fixed point in firm value functions and policy functions using the stochastic algorithm of [41]. Briefly, this algorithm simulates the model a very large number of times, updating firm value functions with the true distribution of observed profits and finding optimal firm policies. With firm policy functions governing exit, entry and type choice, I can then simulate the behavior of firms in different markets and consider the effects of different policies regulating firm conduct.

I start at the true firm distribution in year 2000 and forward simulate 11 years. I repeating this many times and for many markets as a policy benchmark and as an informal test of the performance and fit of the model. In Table 4.15, I compare the true 2012 firm distribution with the results of model simulations and find that the model performs well, only slightly overestimating the number of one and two star chain firms. I then test two potential policies. First, a policy capping chain firms to be no more than 50% of the market, and second, a policy banning all new entry by chains. I choose these policies in part to avoid the question of how policies would treat existing chain firms in 2000. This also keeps the counterfactual market structure closer to being in sample while providing clear implications. The counterfactual firm type distributions that result from these policies are shown in Table 4.16

There are two notable effects of the policy changes. First, while there are naturally fewer chain firms under the potential policies, there are also fewer firms total. This is true despite there being the same number of potential entrants in both scenarios. In the policy banning new chain entrants, the total number of firms in the market falls by 1.03 on average. Second, this fall is most pronounced in the 3 star category, where the mean number of firms falls from 2.3 to .5. This is partially made up for by an increase in the number of 1 star firms. The same result is seen, albeit with smaller magnitudes, in the policy capping chains at 50%.

Given the empirical results presented earlier, this is not a surprise. The chain revenue premium is increasing in quality, and so the option of chain affiliation increases the incentives of new entrants to open a high quality firm. Restrictions on chain affiliation reduce both the total number of firms and their average quality level.

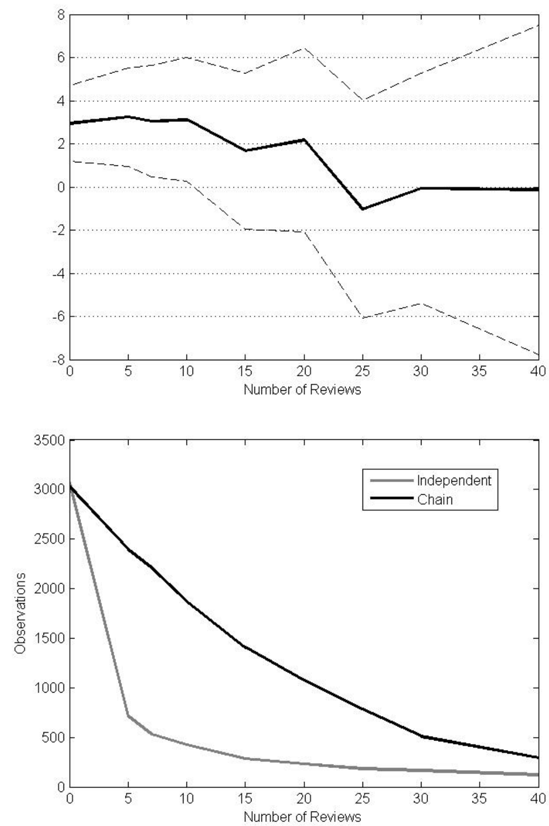
4.5 Conclusion

The rapid growth of chains over the past few decades has attracted the attention of policymakers and economists in a variety of fields. This paper addresses the question of why firms organize into chains at all. It uses high quality firm level data on chain and independent firms in the hotel industry to test the main hypotheses of why chains are successful.

Reduced form analysis of firm revenues show that chains earn a significant premium, and that this premium is consistent with a model of low consumer information. In particular, the chain premium declines over time, appears immediately when a firm joins a chain, and is larger for chains with more outlets. In addition, among firms with large numbers of online reviews, the premium essentially disappears. Altogether the data support the view that chain firms enjoy market power that derives from having a known reputation in settings where consumers have little information about product quality.

In contrast, structural estimates of firm costs suggest chains derive no efficiency advantage from their affiliation. They may even face higher operating costs than independent firms. The cost estimates correspond closely to consultant's estimates of operating costs from survey data, and are robust to numerous different specifications. The evidence thus suggests that the growth of chains in the hotel industry results from market power and not efficiency.

Figure 4.6: Chain Premium, truncated by # Reviews



Note: The top chart presents the estimated chain premium in dollars on the y-axis, where the estimates are on samples truncated by only considering firms with a minimum number number of reviews, shown on the x-axis. The bottom table shows the number of firms in each truncated sample.

Figure 4.7: Growth of Chains in Rural Texas Hotels

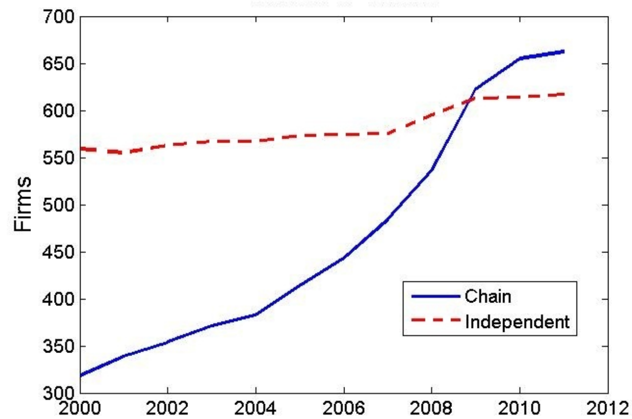


Figure 4.8: Excluded Markets

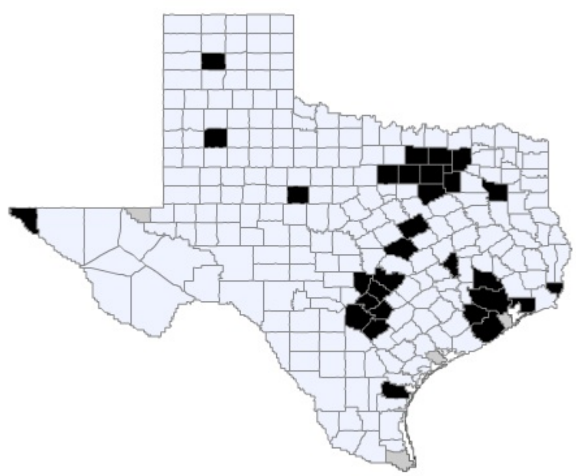


Table 4.2: Hotel Summary Statistics

	Chain	Independent
N	676	627
Rooms		
Total	42,306	27,246
Mean	62.4	43.3
Min	20	20
Max	492	445
Mean RevPar		
Total	32.07	19.07
1 star	20.36	17.44
2 star	28.82	24.04
3 star	42.21	34.08
4 star		44.00

Note: This table presents summary statistics on hotel size and revenue per available room per day (RevPar.) Star ratings are based on the AAA Tourbook.

Figure 4.9: Selected Market Characteristics

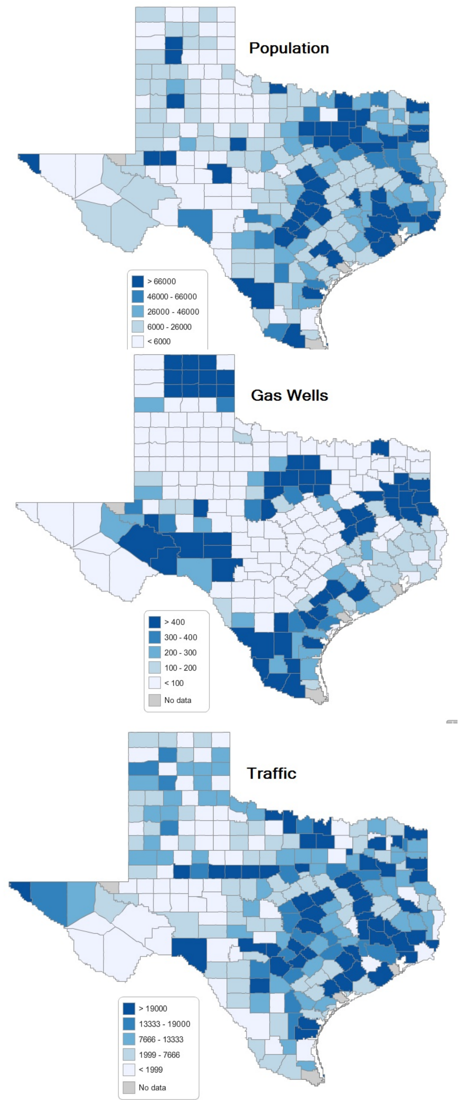


Table 4.3: Revenue Estimates

	Pooled OLS	Market FE	Firm FE
Chain Status	6.450***	5.973***	4.347***
	(.526)	(1.009)	(1.015)
#Competitors	-.052	-.945***	-.964***
	(.042)	(.254)	(.261)
Mkt Chain Share	-6.626***	-9.189***	-6.639***
	(.709)	(2.178)	(2.002)
Log County Revenue	.291	3.718***	3.888***
	(.197)	(.857)	(.851)
Log Capacity	-.043	-2.008*	-18.519***
	(.371)	(1.081)	(2.46)
Log Traffic	-1.129***	.594	2.632
	(.227)	(1.348)	(2.551)
Log Gas Wells	.288***	-.125	-.211
	(.066)	(.421)	(.612)
Δ Gas Wells	3.356***	2.302***	2.120***
	(1.219)	(.796)	(.578)
Log Oil Wells	-.030	.009	-.027
	(.065)	(.343)	(.618)
Δ Oil Wells	-1.924	-1.219	-.731
	(1.334)	(1.076)	(.705)
Log Population	.059	-3.574***	-9.725*
	(.243)	(1.233)	(5.511)
Unemployment	-.484***	-1.768***	-1.582***
	(.099)	(.479)	(.418)
2 Stars	2.489***	3.145*	8.998
	(.684)	(1.659)	(17.642)
3 Stars	18.398***	20.169***	7.548
	(.959)	(3.346)	(18.613)
4 Stars	41.569***	33.691***	
	(2.834)	(11.474)	
1 Stars*User Rating	2.574***	2.645***	
	(.169)	(.494)	
2 Stars*User Rating	3.309***	3.393***	
	(.187)	(.478)	
3 Stars*User Rating	1.572***	1.697**	
	(.235)	(.768)	
σ(Ratings)	-7.459***	-6.669***	
	(.790)	(1.962)	
Year Dummies	Yes	Yes	Yes
cons	20.434	-9.973	101.560
	(2.776)	(12.677)	(54.467)
R^2	.32	.39	.76
N	12,807	12,807	12,807

Notes: The dependent variable is RevPar. Standard errors are in parentheses, they are robust and clustered at the market level for all specifications. All data is annualized and Δ denotes the 1 year change.

Table 4.4: Full Revenue Estimates with Interactions

Specification	I	II	III
Chain Status	-10.55*	.56	-.87
	(5.49)	(1.2)	(1.40)
#Independents	.78***	.73**	.77
	(.23)	(.40)	(.52)
#Chains	-1.80***	-2.89***	-2.78***
	(.17)	(.264)	(.35)
Log County Rev	4.16***	8.23***	8.17***
	(.44)	(.81)	(1.12)
Log Capacity	-1.98***		
	(.36)		
Unemployment	-1.96***	-2.22***	-2.17***
	(.20)	(.29)	(.33)
Log Traffic		3.237***	4.96**
		(1.07)	(2.74)
Log Gas Wells	-.34	-3.52***	-3.56***
	(.28)	(.39)	(1.13)
Δ Gas Wells	1.47*	2.302***	2.120***
	(.84)	(.796)	(.578)
Log Oil Wells	.40	.009	-.027
	(.36)	(.343)	(.618)
Δ Oil Wells	-.43	-1.219	-.731
	(.78)	(1.076)	(.705)
Log Population	-2.05**	4.79***	-6.07
	(.84)	(1.12)	(11.87)
2 Stars	25.86***	5.34***	4.21***
	(5.37)	(1.13)	(1.32)
3 Stars	37.32***	17.93***	26.00***
	(6.23)	(1.32)	(1.69)
User Rating	2.73***	2.81***	
	(.12)	(.19)	
σ(Ratings)	-6.61***		-9.03***
	(.75)		(1.25)
σ(Ratings)*Chain*1 star		-4.37	
		(3.68)	
σ(Ratings)*Chain*2 star		-3.56	
		(2.26)	
σ(Ratings)*Chain*3 star		-7.59***	
		(2.63)	
σ(Ratings)*Unaf*1 star		-10.39***	
		(1.60)	
σ(Ratings)*Unaf*2 star		-11.55***	
		(3.06)	
σ(Ratings)*Unaf*3 star		-7.14	
		(10.33)	
Year Dummies	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes
R^2	.37	.36	.35
N	12,717	6,094	6,094

Notes: Standard errors are robust and clustered at the market level for all specifications. All data is annualized. #Independents and #Chains refer to the number of each type of competitors the firm faces.

Table 4.5: Revenue Effects of Adding or Dropping Affiliation

Specification	All Switchers	C →U	U →C	U →C	U →C
Chain Status	4.39***	.74	6.24***	4.07***	
	(.73)	(1.58)	(1.08)	(1.28)	
Lead of Chain Status				1.82	
				(1.27)	
# Competitors	-.99***	.43	.08	-.93***	-.87***
	(.11)	(.60)	(.42)	(.11)	(.11)
Market Chain Share	-6.82***	-2.07	-9.78***	-6.75***	-4.51***
	(1.09)	(5.75)	(2.70)	(1.07)	(1.02)
Log County Rev	3.62***	.63	7.98***	2.30	
	(.32)	(1.95)	(1.20)	(.32)	
Log Capacity	-18.84***	-17.45***	-16.25***		-18.19***
	(1.06)	(3.85)	(2.51)		(1.04)
Unemployment	-1.69***	-2.64**	-.32	-1.04***	-1.81***
	(.15)	(1.11)	(.66)	(.15)	(.07)
Log Traffic	2.62***	-3.38	8.64**	2.52***	.36
	(.97)		(3.79)	(.92)	(.93)
Log Gas Wells	-.15	1.41	-4.77***	.18	.08
	(.22)	(2.22)	(1.24)	(.22)	(.22)
Log Oil Wells	-.18	1.02	-6.74**	.32	.45
	(.51)	(.40)	(2.66)	(.33)	(.34)
Log Population	-12.28***	4.79***	-3.27	-2.81***	-1.18
	(2.45)	(1.12)	(7.87)	(.91)	(.79)
2 Stars	1.67	5.77	-2.19	-4.10	2.71
	(3.22)	(13.30)	(4.13)	(3.73)	(3.12)
3 Stars	9.48***			2.02	9.22***
	(3.55)			(5.87)	(3.49)
Years before switch:					
5					1.42
					(1.88)
4					1.05
					(1.78)
3					.007
					(1.72)
2					1.24
					(1.68)
1					.40
					(1.65)
Years after switch					
1					4.06**
					(1.82)
2					2.75
					(1.69)
3					2.97*
					(1.70)
4					3.77**
					(1.73)
5					4.62***
					(1.80)
Year Dummies	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	.37	.36	.35	.14	.14
N	12,454	385	739	739	739

Notes: This table analyzes the effects of adding or dropping chain affiliation with firm fixed effects. The dependent variable is RevPar. Specifications labeled "C →U" includes only firms that switch from chain to unaffiliated, and vice versa.

Table 4.6: Chain Only Revenue Estimates

	Market FE	Firm FE
Log Chain size	4.238***	2.367***
	(.251)	(.595)
#Independents	1.516***	.807***
	(.341)	(.289)
#Chains	-.732***	-1.038***
	(.216)	(.184)
Log County Rev	8.738***	8.153***
	(.554)	(.460)
Log Capacity	-9.490***	-22.930***
	(.645)	(1.877)
New Firm	-5.145***	-8.446***
	(.550)	(.618)
Unemployment	-1.832***	-1.839***
	(.149)	(.123)
Log Traffic	3.611*	2.301
	(2.025)	(1.677)
Log Wells	-.387	-.464
	(.438)	(.389)
Log Population	11.158***	10.494***
	(.170)	(3.677)
User rating	2.633***	
	(.170)	
2 Stars	3.744***	
	(.786)	
3 Stars	17.160***	
	(.819)	
N	5669	5669
R^2	.35	.17

Note: This table presents results on the sample consisting only of chain firms. The dependent variable is RevPar.

Table 4.7: Hotel Reviews Summary Statistics

AAA Rating	$\star$	$\star\star$	$\star\star\star$
Chain			
Mean # Reviews	13.25	16.14	24.99
Average Rating	2.72	3.18	3.79
Mean σ(Ratings)	4.30	4.78	11.78
Mean reviews per room	.16	.25	.35
Independent			
Mean # Reviews	13.28	13.82	35.27
Average Rating	2.93	3.04	3.70
Mean σ(Ratings)	4.53	3.72	16.58
Mean reviews per room	.10	.22	.58

Note: This table presents summary information on TripAdvisor.com consumer ratings taken from a December 2012 cross-section, broken down by firm type.

Table 4.8: Estimated Slope of Reviews*Firm Type

	σ(Ratings)	Mean Rating
Independent		
1 star	-10.39***	2.66***
	(1.60)	(.28)
2 star	-11.55***	2.90***
	(3.06)	(.54)
3 star	-7.14	.32
	(10.33)	(.67)
Chain		
1 star	-4.37	4.32***
	(3.68)	(.62)
2 star	-3.56	4.35***
	(2.26)	(.31)
3 star	-7.59***	1.08***
	(2.63)	(.35)
N	6,094	6,094
R^2	.36	.35

This table presents the interactions of firm type and TripAdvisor.com ratings data. The dependent variable is RevPar. Full results are shown in Table 4.4.

Table 4.9: Incumbent Firm's Policy Function

Specification	I	II	III
Chain Status	.360	.409	8.209**
	(.330)	(.331)	(4.09)
#Independents	.091*	.024	.029
	(.053)	(.054)	(.054)
#Chains	-.032	-.015	-.014
	(.038)	(.038)	(.038)
Log County Sales	.017	-.103	-.644
	(.105)	(1.32)	(1.37)
Unemployment	-.065**	.082	-.008
	(.039)	(.140)	(.152)
Log Traffic	-.282**	2.234**	2.056**
	(.126)	(.941)	(1.020)
Log Wells	.077**	.128	.137
	(.032)	(.107)	(.107)
Log Population	.180	3.34***	3.632***
	(.136)	(1.13)	(1.143)
2 Stars	1.047***	1.069***	1.069***
	(.347)	(.346)	(.349)
3 Stars	.885**	.893**	.903*
	(.409)	(.411)	(.413)
(Log Sales)^2		.003	.018
		(.032)	(.033)
(Unemployment)^2		-.010	-.006
		(.008)	(.009)
(Log Traffic)^2		-.145***	-.136***
		(.052)	(.057)
(Log Wells)^2		-.012	-.011
		(.015)	(.015)
(Log Population)^2		-.149***	-.166***
		(.053)	(.053)
Chain*(Log Sales)			-.556**
			(.271)
Chain*(Unemployment)			.187
			(.127)
Chain*(Log Traffic)			-.242
			(.375)
Chain*(Log Wells)			-.083
			(.080)
Chain*(Log Population)			.521
			(.326)
N	12,270	12,270	12,270
R^2	.04	.06	.07

Each specification is a logistic regression. The dependent variable is 1 if the firm is active that period and 0 otherwise.

Table 4.10: Poisson Entry Probability by Firm Type

	Independent			Chain		
	1 star	2 star	3 star	1 star	2 star	3 star
Demand Shifters						
Log County Sales	.744***	.111	-.119	7.235**	.284	.190
	(.23)	(1.99)	(.569)	(3.68)	(.41)	(.29)
Unemployment	-.104	-.070	.035	.228	.005	-.067
	(.07)	(.429)	(.234)	(.48)	(.10)	(.07)
Log Traffic	-.033	10.152	.217	-.006	1.080*	-.873***
	(.28)	(6.26)	(.555)	(1.59)	(.63)	(.32)
Log Gas Wells	.247	3.632**	.221	.199	.069	.899***
	(.19)	(.1.84)	(.204)	(1.23)	(.19)	(.21)
Log Population	-.538	11.155	-.027	-29.389	.017	1.269**
	(.44)	(9.40)	(.105)	(18.12)	(.75)	(.54)
Interest Rate	-.314**	-1.359*	.423	-.733	-.582***	-.848***
	(.28)	(.85)	(.608)	(.88)	(.21)	(.14)
Mean Market Age	.168***	.047	.027	.134	.108	.228***
	(.05)	(.27)	(.105)	(.24)	(.63)	(.05
Number of Existing Firms						
Independents:						
1 star	-.781***	1.707**	.173	.855	.440**	.190
	(.12)	(.84)	(.224)	(.159)	(.20)	(.28)
2 star	.492	-6.207***	.134	-2.208	-.859**	.634*
	(.32)	(1.67)	(.859)	(2.61)	(.38)	(.30)
3 star	-.880	-4.257	2.227	.335	.746	-.667
	(.68)	(3475)	(.763)	(.712)	(.68)	(.50)
Chains:						
1 star	-.220	2.416	-16.481	-4.826***	.250	-.193
	(.41)	(2.06)	(2087)	(1.65)	(.49)	(.35)
2 star	-.255	-3.436***	.057	-1.978*	-1.905***	.406**
	(.20)	(1.16)	(.411)	(.205)	(.25)	(.16)
3 star	-.302**	.495	-.515	.558	.544***	-1.074***
	(.13)	(.90)	(.645)	(.75)	(.15)	(.10)
N	2729	2729	2729	2729	2729	2729

Each column represents a poisson regression on the number of entrants of each firm type in each market each year. Independent variables are market characteristics and the number of firms already in the market by type of firm.

Table 4.11: Estimated Operating Costs ($ per room per day)

Constant	21.85***	21.57**	21.97***
	(6.23)	(10.17)	(8.95)
Chain	3.73*	3.70**	
	(1.93)	(1.68)	
2 star	7.87***	7.87***	7.84*
	(1.93)	(2.15)	(2.53)
3 star	20.22***	20.19***	20.25***
	(2.51)	(2.43)	(2.23)
Log(Capacity)		.08	
		(.66)	
Chain size $<$ 100			4.62***
			(1.88)
100 $<$ Chain size $<$ 200			3.11
			(2.37)
200 $<$ Chain size			3.67
			(2.12)

This table presents final stage estimates of firm operating costs, expressed in terms of dollars per room per day, with bootstrap standard errors. Chain size refers to the number of chain partners in Texas.

Table 4.12: Estimates Using Different First Stage Specifications

	Logit	Probit	Poisson
Constant	21.85	22.35	19.53
Chain	3.73	3.70	2.45
2 star	7.87	7.93	5.54
3 star	20.22	20.22	18.03

This table compares the results of final stage costs estimation under different first stage specifications of policy functions. I model entry/exit decisions as logit, probit and poisson processes and solve the final stage using each as inputs.

Table 4.13: STR Operating Costs ($ per room per day)

Administrative	3.31
Marketing	.64
Utilities	2.66
Maintenance	2.24
Total Operating Expenses	8.85
Franchise Fees	1.99
Management Fees	.65
Property Taxes	1.99
Insurance	.65
Debt Service and Other	14.18
Payroll and Related	7.97
Total	31.00

Notes: Data from Smith Travel Research 2012 Hotel Operating Statistics Study, which compiles survey data from 3,593 limited service hotels across the U.S. in the preceding year. Operating costs are for limited service hotels in the Budget category.

Table 4.14: Cost Estimates ($ per room per day)

	No Market Effect	Market RE
Constant	21.85***	22.57***
	(6.23)	(3.81)
Chain	3.73*	.20
	(1.93)	(3.07)
2 star	7.87***	7.16***
	(1.93)	(2.51)
3 star	20.22***	19.16**
	(2.51)	(7.05)

This table compares final stage operating cost estimates with and without controlling for market level unobservables.

Table 4.15: Comparison of Model Simulations to Data

Firm Type	True Firm Distribution	Simulated Firm Distribution
Independent		
1 star	3.89	3.74
2 star	.49	.48
3 star	.14	.14
Chain		
1 star	.10	.40
2 star	1.26	2.08
3 star	2.17	2.08

The left column is the distribution of firm types in 2011 in the data. The right column shows the results of model simulation. For each market, the model is started at the true 2000 distribution and forward simulated $10,000$ times.

Table 4.16: Counterfactual Firm Distributions

Firm Type	No Limit	50% Rule	No Chain Entry
Independent			
1 star	3.89	4.26	5.01
2 star	.49	.49	.49
3 star	.14	.14	.20
Chain			
1 star	.10	.09	.09
2 star	1.25	1.25	1.24
3 star	2.17	1.76	.28
All			
1 star	4.29	4.35	5.10
2 star	1.74	1.74	1.73
3 star	2.31	1.90	.48
Total	8.34	7.99	7.31

This table considers the results of potential policy changes on the counterfactual firm distribution. It presents the mean number of firms of each type in each market, computed over many simulations at many markets under different policy scenarios.

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