Capacity and Collusion:

An Empirical Analysis of the Texas Lodging Industry

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Abstract

Research suggests that firms' idle capacity might provide an effective threat of price wars and hence promote tacitly collusive pricing. Additionally, the distribution of idle capacity is also likely to influence tacitly collusion. For example, the more symmetrically distributed the idle capacity among firms in the industry, the less likely it is that any one firm has a disproportionate incentive to cut prices, and the more likely it is that other firms can effectively retaliate, hence leading to higher equilibrium prices. We use a panel dataset of the Texas lodging industry from 1991-1997 to test some of these predictions on the capacity-collusion relationship. We find that increasing market concentration increases price and increasing the concentration of market idle capacity decreases price. Alternative explanations of non-strategic reasons to carry idle capacity e.g. lumpy capacity additions, demand uncertainties, and peak-load pricing appear unlikely to be driving our results.

Key words: Capacity, collusion, hotels.
JEL classification: L13 (oligopoly and other imperfect competition markets), L85 (real estate services), M21 (business economics)

1. Introduction

Of the various competitive tools, capacity choice is often the most irreversible. Therefore, the choice of capacity can have a longer-lasting and more intense impact on competition in a market than pricing or advertising or even new product introductions, which are easier to reverse. The effect of capacity on competition (or pricing power), depends on the reason for why idle capacity is carried in the first place. [1] There are two competing hypothesis here. First, total industry capacity and idle capacity might have an impact on the ability to tacitly collude in the industry, and hence there might be a strategic role for excess capacity in sustaining collusive pricing. Second, excess capacity could be carried by players for non-strategic reasons and therefore not likely to have a strategic impact on pricing. For example, lumpy capacity addition technologies, demand variability, demand uncertainty etc. influence industry concentrations and pricing, even outside of the impact on collusion. Various theoretical papers have addressed how these two alternative mechanisms play out. It is harder to find work that contrasts or combines these two alternative mechanisms.

Empirical tests of the effect of capacity on price are rare (Rosenbaum (1989), Iwand and Rosenbaum (1990), and Roller and Sickles (2000) are exceptions).[2] To test the effect of capacity on the ability of firms to collude, firm-level prices and capacities are required (especially for industries that produce a heterogeneous product). Additionally, data on controls for firm level demand and cost conditions are also needed to isolate the competitive effects of capacity on pricing. These data are needed for each firm in the industry. Another prerequisite is that the capacity be reasonably irreversible in this industry and not easily transferable across markets. Identifying such an industry and obtaining such data is not trivial. In addition, given the difficulty in building a structural model of firms' capacity and price choices that could include reasons to carry capacity and idle capacity, the researcher has to rely on reduced-form tests and yet be able to contrast predictions of the strategic elements of capacity-collusion links versus the non-strategic capacity-pricing links.

We have put together a panel dataset from the Texas lodging industry to empirically test the effect of capacity on pricing. We have annual data from 1991 through 1997 on all lodging properties in Texas with annual revenue over $13,000. The data consist of price, quantity, capacity, location, taxpayer identification and brand affiliation at the property level as well as travel expenditures, tax rates, retail wages, population, per capita income and construction wages at the city or county level. The property level information and the panel aspect of the dataset allow us to account for property-specific fixed effects in our empirical estimation.

In going from the data to an empirical test, we test implications from the literature on strategic reasons to carry idle capacity. An important insight from this literature is as follows- in addition to the level of idle capacity in the industry, the distribution of idle capacity also influences the ability to reach tacitly collusive pricing. For example, the more symmetrically distributed the idle capacity among firms in the industry, the less likely it is that any one firm has a disproportionate incentive to cut prices, and the more likely it is that other firms can effectively retaliate, hence leading to higher equilibrium price. We estimate reduced-form demand and pricing equations, accounting for property-specific and time fixed effects. We find evidence that increasing market concentration increases price and increasing the concentration of market idle capacity decreases price. These results are robust to a variety of demand, cost, and market specifications. We discuss how alternative explanations of non-strategic reasons to carry idle capacity e.g. lumpy capacity additions, demand uncertainties, and peak-load pricing are unlikely to be driving our results.

The rest of the paper is organized as follows. Section 2 discusses the main testable hypotheses from the literature on the impact of capacity on pricing power. In section 3, we describe the data. Section 4 discusses how we apply our data to test the capacity-tacit collusion link, and discusses our empirical model. Section 5 has results and robustness tests, and explores alternative explanations for our findings. We conclude in section 6.

2. Predictions on the Capacity-Tacit collusion Link

Game theory suggests that in a single-period game, firms will revert to a static Nash equilibrium. Repetitions of the game can result in more profitable outcomes for firms, as modeled by the supergame literature. In pioneering work, Friedman (1971) shows that in repeated games, the threat of reversion to a static Nash equilibrium can help sustain collusion in industries. Subsequent work (among other things) expands the strategy space (Abreu (1986)) and introduces demand uncertainty (Green and Porter (1984)).

As our principal interest is in exploring the effects of capacity on price, one of the earliest models relevant to our work is Brock and Schienkman (1985). They examine a supergame where the capacity of each price-setting firm is fixed. They discuss how idle capacity influences both the incentive to deviate from collusive pricing and retaliation possibilities available to firms. They show that for symmetric firms, the highest sustainable per capita profit varies non-monotonically with the number of firms. This is because as the number of firms increases, the threat that the remaining firms can impose on a defecting firm increases, thereby dissuading any firm from defecting. However, as the number of firms increases further, the collusive profits per firm decreases, tempting firms to defect. They also show that price decreases as idle capacity increases. Benoit and Krishna (1987) endogenize the capacity choices of firms, and extend the Kreps-Scheinkman model (1983) to allow the price game between firms to be an infinitely repeated, so as to allow the equilibrium existence of tacit collusion. Kuhn (2006) shows that fragmentation can facilitate collusion when no firm has the capacity to serve the entire market demand, limiting gains from defection. His theory is consistent with Sweeting's (2005) finding that fragmentation of the English and Welsh electricity markets led to higher profits.

In an important extension of this literature, Davidson and Deneckere (1990) examine a class of equilibria where asymmetric firms choose capacity competitively, but are allowed to achieve tacit collusion in pricing. They find that asymmetric duopolies might find it harder to sustain tacit collusion because the larger firm has more of an incentive to cut price, and the smaller firm is unable to retaliate effectively (see also Lambson 1994 for a generalization to multiple firms and more general punishment strategies). Compte, Jenny and Rey (2002) also find that asymmetric capacities make collusion harder when the aggregate capacity is limited. However, when aggregate capacity is much larger than the market size, asymmetries might make collusion easier because the smaller firm can effectively cover the market in a retaliation stage, thereby dissuading the larger firm from deviating from collusive pricing. A caveat here is that the smaller firms not be too small to cover the market, or be impaired in any other way to cover the market (e.g. high levels of horizontal or vertical differentiation favoring the larger firms). If they are indeed unable to cover the market, then asymmetric capacities will continue to make collusion harder. Vasconcelos (2005) argues that symmetry of firms causes more collusion but via a very different mechanism. He argues that the smallest firms cause the highest competitive pressure given they have the most to gain via business stealing (even if they cannot cover the market), and the largest firms are least likely to follow punishment strategies given they have the most to lose in punishment phases.

This stream of research has been developed in two further ways. Besanko and Doraszelski (2004) explicit model dynamic capacity choice games via Markov-perfect Nash equilibrium games. They show that for a homogeneous duopoly case, asymmetric firm sizes might arise endogenously in industries where capacity choices might have some reversibility in them. In such industries, among two ex-ante symmetric firms, a firm can move first to accumulate capacity. Given this, the follower firm finds it more profitable to play "puppy dog" and stay small. In such markets, firm asymmetries and collusive prices co-exist. For a differentiated goods duopoly, the authors show that firm size differences (and collusive pricing) decline slowly as goods become more differentiated; the results are robust to extending to three firms, but generalizations for more firms are not available. Note that this paper does not have implications for excess capacity being used to collude but instead has implications for size distribution of firms and collusion.

Another development in this literature is modeling supergames where price and quantity are set simultaneously rather that the sequential choice studied in the literature previously. Dechenaux and

Kovenock (2003) show that in such games too it makes sense for the smaller firm to stay small, have lower prices and yet not utilize its entire capacity (i.e. play judo economics) in order to prevent the larger firm from defecting. Therefore, in equilibrium, size and price dispersion exist, yet average prices are higher due to this tacit collusion. This paper also does not have clear implications for the relationship between excess capacity and collusion but rather between capacity and collusion.

For our purpose, there are two broad testable hypothesis from this literature (1) examining the relationship between industry concentration and price. The oligopoly literature predominantly predicts a positive relationship (2) the relationship between the distribution of idle capacity and price might negative if the smaller firm cannot effectively cover the market in a retaliation stage. The discussion above suggests that this relationship could be positive or negative, depending on the distribution of capacity among firms relative to industry demand.

3. Data

In order to test the relationships between price and concentration, price and idle capacity, and price and the distribution of idle capacity, we have collected annual information on every lodging property (i.e., hotels, motels and bed and breakfasts) in Texas with annual revenue over $13,000 from 1991 through 1997. While having limited information on the physical characteristics of each lodging property, the panel nature of the dataset allows us to account for property-level fixed effects in our estimation. These property fixed effects capture the properties' physical characteristics that do not vary across years. We have augmented the property-level information with city- and county-level information. In the rest of this section, we describe these property and market-specific variables.

We first discuss the market-level data. These consist of demand and cost shifters that are common to all properties in any market. As there can be several possible classifications of a market-counties, cities, extended stay properties, budget properties, etc., we have attempted to get data for as fine a market definition as possible. The market-level data consist of city-level information on tax rates as well as county-level information on travel expenditures, retail wages, population, per capita income and construction wages. The Texas Department of Economic Development's Tourism Division annually publishes *Texas Local Hotel Tax.* This report provides city-level hotel tax rates for approximately 350 of the larger cities. For those properties in cities that were omitted from the report, tax rates were obtained by calling at least one hotel in each of the omitted cities. The Tourism Division also publishes *Travel Spending for Texas Counties.* This report contains annual travel expenditures and retail wages for each of the 254 counties in Texas. The travel expenditures and retail wages are computed using The Travel Economic Impact Model developed by the U.S. Travel Data Center and are based on expenditures, employment and payrolls in 14 travel-related businesses. Finally, population and per capita income are obtained from the United States Census Bureau and construction wage is obtained from County Business Patterns (U.S. Department of Commerce).

The second set of variables consists of property-level data. This information includes price, quantity (rooms sold), capacity (rooms), location, property ownership, and brand affiliation. The Texas State Comptroller requires every lodging property to report taxable and non-taxable revenues on a quarterly basis.[3] Source Strategies Incorporated (SSI), an independent marketing research firm located in San Antonio, aggregates and augments this (public) information in their annual reports entitled *Texas Hotel Performance Factbook*. In addition to information on property name, capacity, and revenue, SSI's *Factbooks* contain information on each property's average daily room rates (ADR), brand affiliation and the number of days the property is opened throughout the year. ADR is estimated from surveys conducted by SSI, financial reports, information from appraisers, chain and AAA directories, and information provided by Smith Travel Resource.[4] This ADR data is the pre-sales tax price. Total rooms sold each year can then be calculated by dividing total revenue by ADR. The information from SSI's *Factbooks* is matched to taxpayer information obtained from the State of Texas Comptroller's office. This taxpayer information allows us to identify properties which are under the same ownership. In addition, these tax records, along with information obtained from the 1991 through 1997 *Directory of*

Hotel & Motel Companies and a phone survey, provide a cross check on properties' brand affiliations reported by SSI.[5] Finally, brands are categorized into sectors (Full-Service, Limited-Service or Extended Stay) and segments (Deluxe, Luxury, Upscale, Midscale with Food and Beverage, Midscale without Food and Beverage, Economy, Budget, Upper-tier Extended Stay and Lower-tier Extended Stay).

Table 1 contains the descriptive statistics.

--------Insert Table 1 here--------

Besides number of properties, the values in Table 1 are averages over all properties which exist in the specific year. All appropriate values have been converted to 1996 dollars. As the first panel of the table indicates, the number of properties and the average annual price have increased substantially across years while the average daily capacity (i.e., average number of rooms) has remained relatively constant across years. In addition, percent idle capacity (calculated by dividing total number of rooms unsold in the year by total number of rooms available in the year) has decreased from 44.7 percent in 1991 to 40.2 percent in 1997. This suggests that the demand for and supply of lodging in Texas have increased from 1991 to 1997. The first panel of Table 1 also indicates that the percent of daily capacity attributable to entry and the percent associated with properties that exit are non-negligible.[6] The average number of rooms of entering properties is 46.1 and of exiting properties is 27.6. This suggests that entry and exit is more prevalent among the smaller properties such as bed and breakfasts. Finally, travel expenditure, population, per capita income, tax rate and construction wage have increased across the years.

In addition to market idle capacity, the two variables of primary interest in our empirical specification are the concentration and the distribution of idle capacity in the market. The Herfindahl index based on taxpayer yearly capacity is used as the measure of concentration and calculated in the second panel of Table 1 using four different market definitions.[7] The Herfindahl index based on taxpayer yearly idle capacity is used as the measure of the distribution of market idle capacity and is presented in the third panel of Table 1 using the same market definitions.[8] The four market definitions are based on geographic location (city or county) and the classification of the lodging property (segment or sector).

Properties that are not affiliated with a brand (i.e., independent) are considered in the same segment and sector. These are the four market definitions used to empirically test the implications of capacity-tacit collusion literature. As expected, the Herfindahl indexes are larger when the market definition is based on city compared to county and segment compared to sector. Also note that the Herfindahl indexes based on taxpayer yearly capacity and taxpayer yearly idle capacity decrease slightly over time for almost all market definitions.

4. Empirical Model

4.1: Incorporating the empirical realities of the lodging market

To examine the capacity-tacit collusion link, we estimate property-level reduced-form demand and pricing equations. We cannot estimate the exact relationships between price and number of firms, or price and percent idle capacity in various theoretical models because various features of the lodging industry make it highly unlikely that these precise relationships will hold. For example, it appears unlikely that trigger strategies (e.g. as in Brock and Scheinkman, 1985) in the lodging industry. Some other differences between theoretical model settings and the empirical realities of the lodging market include differentiation among properties, growth in markets and varying prices over time. We detail these below.

Horizontal differentiation can be in terms of location, size, brand affiliation, types of services available and type of accommodations provided. For example, some lodging properties offer services and accommodations that appeal to the business traveler, while others cater to the extended stay travelers, while still others offer amenities such as swimming pools and playgrounds to attract families. The variety of services and accommodations offered also result in vertical differentiation in the lodging industry.

Also, the lodging market is growing over the time period of our data, as discussed in the previous section. Throughout the 1990’s, there has been substantial growth in the demand for and supply of lodging properties in Texas. This growth in demand has been especially high in urban areas. The increase in supply is primarily the result of new properties entering the market but also of existing properties expanding their number of rooms. Eleven-hundred and four properties have entered while 882 properties have exited from 1991 through 1997.

Besides demand and supply, markets have changed over time in regards to brand affiliation. The percent of lodging properties that are brand affiliated has increased from 31.7 in 1991 to 49.5 in 1997. See Conlin (1999) for a detailed analysis of these market changes. In the hotel industry, firms do not charge a single price for all rooms the entire year. Various types of customer segmentation strategies exist such as by consumer type and time of year. For example, lodging properties often offer discount rates for convention participants, AAA members and AARP members. Lodging property rates also frequently vary depending on the day of the week and the season of the year.

These features of the lodging market influence our empirical testing of whether there is any capacity-tacit collusion link. We account for these departures by including in the empirical specification property-level fixed effects, yearly fixed effects, and demand and cost shifts resulting from changes in market conditions. We explain these below.

Property-level fixed effects control for information on differentiation likely to influence both demand and cost, and information that is absent from our data, e.g. the presence of a conference center, a swimming pool, exercise facilities or a complementary breakfast. Furthermore, the asymmetries among firms result in the Herfindahl index based on taxpayer capacity being used as the concentration measure and the Herfindahl index based on taxpayer idle capacity being used as the measure of the distribution of idle capacity.

Note that property level fixed-effects do not control for characteristics of a property that vary across years. While this is likely the case for many lodging properties in Texas, other properties have undergone major changes in the 1990s. The properties whose characteristics vary across years are likely those whose days open, capacity or brand affiliation change across years.[9] We could include changes in days open, capacity and brand affiliation in our demand and supply equations but the effect of these changes are likely to depend on the property. For example, a property that changes brand affiliation may increase or decrease its demand and costs depending on whether the change is to a brand of higher or lower quality. Properties that change their days open, capacity or brand affiliation are often the ones that experience large changes in price and quantity across years. Therefore, instead of including these variables in our specification, we drop all property-year observations where the property changed their days open or their number of rooms by more than fifteen from the prior year, or changed their brand affiliation from the prior year.[10] Property heterogeneity and a single taxpayer often owning multiple properties in the same market are the reasons we use a Herfindahl index based on taxpayer capacity as our concentration measure instead of the number of firms.

The empirical specification accounts for market changes in several ways. First, we control for those factors that change the demand and costs of all lodging properties in Texas by including time dummies in the demand and pricing equations. These yearly dummies do not account for those factors that affect the demand and costs of only properties in certain markets. Therefore, besides including own price in the demand equation, we include the average price of all other properties in the market, county travel expenditures and room tax rates. While the demand specification is a simple one with the same own-price and one-cross price coefficient for all properties in the same market, we conduct numerous functional form tests (See Section 5.2). An increase in travel expenditures in the county and a decrease in the tax rate will likely increase the demand for lodging properties in the market. In the pricing equation, we include rooms sold and retail wage in the county as our cost shifters along with variables that are likely to affect the level of collusion in the market. Another factor that is likely to affect the level of collusion is market entry and exit. We control for the effect of entry and exit on the level of collusion by including the change in market capacity from year t-1 to year t in the supply equation.

Besides market changes, another issue that arises in the estimation is market definition. The horizontal and vertical differentiation that occurs in the lodging industry makes it difficult to accurately define a market. Therefore, we consider four different market definitions. As discussed in Section 3, these market definitions are based on city and county as well as segment and sector location. All lodging properties in the same city-segment, county-segment, city-sector or county-sector (depending on the market definition) are considered in the same market. The estimates of the property-level demand and supply equations based on all four market definitions are presented.[11]

While price discrimination is prevalent in the lodging industry, our dataset contains only the average yearly price of each property. This limitation in our dataset is not likely to bias our results if properties do not vary their price discriminating policies across years. If this is the case, these price discriminating policies will be captured by the property-level fixed effects.

If there does exist some type of tacit collusion in the Texas lodging industry, the equilibrium outcome does not result in the even distribution of idle capacity throughout the market. We use a Herfindahl index based on taxpayer idle capacity as our measure of this concentration of idle capacity.

Because the Texas lodging industry does not directly and exactly correspond to any theoretical model of capacity-tacit collusion link, we estimate continuous linear relationships between price and Herfindahl index (based on taxpayer capacity), and price and percent idle capacity. Based on predictions in the literature, we expect a decrease in this Herfindahl index and an increase in percent idle capacity to decrease the price that can be maintained through tacit collusion. In regards to the concentration of idle capacity, we expect an increase in the Herfindahl index based on taxpayer idle capacity to decrease price.

4.2 Empirical Specification

Because we consider supergames and do not restrict the strategy space, we do not estimate a structural supply or pricing equation. Instead, we estimate a reduced-form pricing equation as a function of cost parameters, the Herfindahl index based on capacity, the percent market idle capacity, the Herfindahl index based on idle capacity, and the change in market capacity. The estimating equations comprise the following demand and reduced-form pricing equation:

$$q_{i,m,t}= a_i+ a_m+ a_t+ b_1*p_{i,m,t}+ c_1*pavg_{m,t}+ d_1*travex_{m,t}+d_2*tax_{m,t} \qquad (1)$$

$$p_{i,m,t}=g_i+g_m+g_t+h_1*q_{i,m,t}+j_1*retailw_{m,t}+k_1*HI_{m,t}+k_2*idlecap_{m,t}+k_3*HIidle_{m,t}+k_4*chmcap_{m,t}$$

where i = lodging property subscript, m= market subscript, t = year subscript, q = average daily number of rooms sold, p = average own price, pavg = average competitor price in the market, travex = travel expenditure in the county, tax = room tax in the city, retailw = retail wage in the county, HI = Herfindahl index based on taxpayer capacity, idlecap = percent idle capacity in the market, HIidle = Herfindahl index based on taxpayer idle capacity, and chmcap = change in market capacity from year t-1 to year t. In Section 5, after the discussion of results, we discuss some functional form robustness checks of the above system.

To conserve data by avoiding estimating property fixed effects, we first-difference the estimating equations to estimate the following

$$\begin{aligned} q_{i,m,t} &= q_{i,m,t-1}+(a_t-a_{t-1})+b_1*(p_{i,m,t}-p_{i,m,t-1})+c_1*(pavg_{m,t}-pavg_{m,t-1}) \\ &\quad +d_1*(travex_{m,t}-travex_{m,t-1})+d_2*(tax_{m,t}-tax_{m,t-1}) \qquad (2) \\ p_{i,m,t} &= p_{i,m,t-1}+(g_t-g_{t-1})+h_1*(q_{i,m,t}-q_{i,m,t-1})+j_1*(retailw_{m,t}-retailw_{m,t-1})+k_1*(HI_{m,t}-HI_{m,t-1}) \\ &\quad +k_2*(idlecap_{m,t}-idlecap_{m,t-1})+k_3*(HIidle_{m,t}-HIidle_{m,t-1})+k_4*(chmcap_{m,t}-chmcap_{m,t-1}) \end{aligned}$$

The endogenous variables are current and lagged values of price, quantity, average competitor price, percent idle capacity, and the Herfindahl index based on idle capacity. The exogenous variables are current and lagged values of travel expenditure, tax rate, retail wage, change in market capacity, and Herfindahl index based on taxpayer capacity.[12] Other instruments are current and lagged values of per capita income, population, and construction wage, as well as double-lagged values of travel expenditure, tax rate, per capital income, population, construction wage and retail wage. We use per capita income, population and construction wage as instrumental variables and not as demand and cost shifters. This is because while unlikely to capture demand and cost shifts, these variables are likely to be good indicators of county activity. In addition, the change across years in this annual information (obtained from the U.S. Census Bureau and the U.S. Department of Commerce) may be quite noisy.

5. Results

5.1 Empirical Results

Table 2 presents the estimation results for the city-segment, county-segment, city-sector and county-sector market definitions. While the coefficient estimates are not reported in the table, the specification includes both property and yearly fixed effects. The results have been divided as demand- and pricing-equation estimates.

----Insert table 2 here-----

First, we discuss the demand parameters. Note that almost all coefficient estimates in the demand equation have the expected sign and most are statistically significant. The own-price effect is negative for three of the market definitions and statistically significant when a market is defined based on segment. When the market definition is county-sector, the own-price coefficient is very close to zero. The positive and statistically significant coefficient on travel expenditure indicates that an increase in county travel expenditures increases the demand for properties in the county. Room tax has the expected negative effect on demand and the coefficient is statistically significant for all market definitions. The cross-price coefficient is always positive and statistically significant for two market definitions. While not reported in the table, many of the year dummy coefficients are relatively large and statistically significant.

In the pricing equation, the sign of the own quantity coefficient depends on market definition. We expected a negative coefficient due to economies of scale which exist in the lodging industry. The retail wage coefficient is negative and statistically significant. The unexpected sign of this coefficient may be the result of inaccuracies in the U.S. Travel Data Center's model. The coefficient associated with change in market capacity is positive for three of the market definitions and statistically significant when a market is defined based on county. While we expected an increase in rooms to decrease the price, this variable could be capturing some omitted market demand or cost variables and possibly expectations of future market growth. The positive coefficient can also be explained by the fact that entry is more likely in markets with high expected growth and a more collusive agreement can be maintained among properties in markets expecting growth (Rotemberg and Saloner, 1986; see too Knittel and Lepore 2006 for an extension with endogenous capacity choices). Several of the year dummy coefficients are statistically significant, indicating that yearly effects are important for the pricing equation.

The coefficients we are most interested in are those associated with HI, idlecap and HIidle. We expect the HI coefficient to be positive, the idlecap coefficient to be negative and the HIidle coefficient to be negative if smaller firms in the market are unable to credibly threaten larger firms from deviating. In all four market definitions, the HI coefficient is positive and the HIidle coefficient is negative. In addition, the coefficient estimates are statistically significant in all market definitions. These results suggest that price increases as a market becomes more concentrated and as the idle capacity in the market becomes less concentrated. These finding are consistent with Compte, Jenny and Rey (2002) when smaller firms do not have adequate capacity to cover the market. Given the quite large levels of idle capacity in the industry (ranging from 40.2% to 44.7% over our time period), it appears possible for some smaller firm to credibly threaten to cover the market. However, the average level of HIcapacity across all years and market definitions is about 3100, which can be consistent with a fairly highly concentrated industry. For example, capacity shares of (40%, 30%, 20%, 5%, 5%) among 5 firms in the industry would result in an HIcapacity of 2950 (less than our market average, so our example is a conservative one). It appears unlikely that the smallest two firms with shares of 5% each can effectively threaten to cover the market in a retaliation phase. Therefore, given the levels of HIcapacity in our industry, smaller firms likely do not have the ability to effectively threaten retaliation. This in turn means that the more concentrated the HIidle, the lower the prices (note that this is after controlling for HI i.e. how concentrated the industry is in quantity-based market shares).

5.2 Robustness checks

We conduct two types of robustness checks. First, we test whether the results presented in Table 2 are robust to alternative demand and pricing specifications. Second, we test whether changing the set of observations used in the estimation affects the results. The coefficient estimates presented in Table 2 are based on only property-year observations where the property did not appreciably change their days open or number of rooms and did not change brand affiliation from the prior year.

First, we discuss the demand-side robustness checks. The first set of specification checks pertains to the variables included in the demand specification. The original specification includes travel expenditure and tax rates as the only market variables that shift demand. We estimated the demand and pricing equation system by also including per capita income and population as demand shifters. In all four market definitions, the coefficients associated with per capita income and population are positive and negative, respectively. Furthermore, these coefficients are statistically significant. The estimates of the coefficients of the other demand variables change little with the own-price coefficient being slightly negative in the county-sector market definition. None of the primary parameters of interest in the pricing equation (i.e., those related to the Herfindahl indexes and idle capacity) change in sign or statistical significance.

The second set of specification tests deals with the pricing equation. First, we include construction wages in the pricing equation. The coefficient on construction wage is negative and significant for all four market definitions. While including construction wage does not change the signs of the coefficients associated with the Herfindahl indexes and idle capacity, it does affect their statistical significance under some market definitions. Another alternative pricing specification is for entry and exit to be included separately in the price equation. The specification in Table 2 includes the change in total number of rooms in the market across years which does not account for property turnover. When the change in rooms is replaced by the total rooms that enter and exit the market, the signs and statistical significant of the coefficients do not change appreciably for any of the market definitions. The coefficients associated with total rooms that enter and total rooms that exit vary in sign depending on the market definition. Under most market definitions, these coefficients are not statistically significant. The final robust checks on the pricing equation concern the Herfindahl index based on taxpayer capacity. The results in Table 2 change slightly when this Herfindahl index is considered endogenous. While the HI and HIidle coefficients do not change signs or statistical significance, the idlecap coefficient becomes statistically significant when market definition is based on segment. When the Herfindahl index is based on taxpayer quantity and considered endogenous, the coefficient estimates are almost identical as those obtained when the Herfindahl index is based on taxpayer capacity.

The final robustness check considers the set of observations used in the estimation. Instead of excluding those property-year observations that change their days open or their room capacity by more than fifteen, we exclude properties that change their days open or their room capacity by more than twenty, more than ten, and more than five. In all cases, the coefficient estimates do not change appreciably from those reported in Table 2. We also estimate the specification excluding all property observations where there was a change in days open of more than fifteen days, a change in rooms of more than fifteen or a change in brand affiliation in any year. This differs from the set of observations used to obtain the estimates in Table 2 because if a property changes brand affiliation at the start of year t, all yearly observations for this property are excluded instead of only the year t observation. When these additional observations are excluded, the signs of the HI, idlecap and HIidle coefficients do not change from those reported in Table 2. However, the number of property-year observations used in the estimation decreases, causing several of the coefficients not to be statistically significant under certain market definitions. Finally, all observations are included in the estimation with days open, capacity and change in brand affiliation included in the demand and supply equations. While several of the coefficients included in the base specification change signs and statistical significance (most notably, own-price and average competitor price), the HI, idlecap and HIidle coefficients do not change appreciably in terms of magnitude. In addition, these coefficients remain statistically significant when a market is defined based on sector.

Summarizing the results from the above tests, the base specification (2) appears to parsimoniously capture relevant parts of the theoretical capacity-tacit collusion literature. The results obtained from this are robust to a variety of alternative specifications of the estimated model.

5.3: Alternative explanations

As we mentioned in the introduction, there are reasons outside of tacit collusion why we might observe certain relationship between capacity and price. In this section, we explore some of these other reasons and discuss why these alternative explanations will not generate our observed data patterns.

An important characteristic of capacity is its frequent lumpiness. That is, if firms expect demand to increase in future, a plausible assumption in the growth markets for Texas lodging, then they invest now, and given lumpiness, idle capacity results. If there economies of scale in capacity addition or if capital market are not perfect, only large firms to be will be able to enter the market successfully. This would enable us to obtain the result of high concentration in markets. If firms price to recover their fixed costs and are able to do so because of entry barriers referred to earlier, the lumpier the technology, the higher the prices. Therefore, a positive correlation between prices and concentration could be obtained because of lumpiness. Lambson (1987) also demonstrates that the larger the scale economies, the higher the industry prices can be, without fear of entry.

A mechanism for why lumpy additions would lead to more concentrated idle capacity is harder to generate. Consider one candidate: if firms all any size have equal probability of filling a room (i.e. perfect competition), then larger firms will be left with larger unused capacity. The more lumpy the addition, the more likely it is we will see this. If firms price to cover fixed costs, the more lumpy the addition, the lower the prices. Therefore, we can get both high concentration of idle capacity and lower prices. However, in the lodging industry, it is hard to believe any model of perfect competition given the vast horizontal and vertical differentiation available. Summarizing, it appears that lumpiness alone cannot generate our second result of idle capacity concentration and lower prices.

Another cause for idle capacity is demand variability. The more variable the demand, the greater the chances of observing idle capacity, ceteris paribus (e.g. given a level of cost of capacity, ability to shift demand around, etc). Suppose there are 2 seasons- high and low. Suppose marginal costs are constant up to a capacity constraint. One can imagine a zero-profit equilibrium in which all firms are at their capacity constraint during the high season and price at marginal cost in the low season. Firms enter until variable profits during the high season equal fixed costs. Average prices exceed marginal cost in this equilibrium, but there is no collusion. Now consider what happens when demand variability increases. Suppose demand during the higher season is higher. Then price and number of firms will both increase until a new equilibrium is reached. The average price in the market (averaged across the year) will be higher because more rooms are sold at the high price. Idle capacity will be higher as well, because the number of firms increased and demand in the low season did not change. So there is a positive relationship between idle market capacity and annual prices. But this is because of demand variability and not collusion. Modifying this a bit, including economies of scale argument here, only larger firms would enter the market and then we would get larger firms and higher prices, our first result. However, like the lumpy capacity addition story, we are unable to provide a mechanism by which demand variability alone would generate higher concentration of idle capacity and lower prices.

Demand variability could also cause idle capacity when firms face different demand shocks, or that firms are partially local monopolists. We might expect each of them to carry idle capacity when seen across a year average, and get higher prices the more the local monopoly they are. Given our regression has property fixed effects, and we have measured the effects of capacity on price for different market definitions that allow for varying degrees of locational market power, this explanation seems unlikely to be generating our results.

Yet another explanation for idle capacity is demand uncertainty. Dana (1999) shows how when capacity is costly and prices are set in advance, the more uncertain the demand, the better off the firm is in offering a variety of prices. For example, in airlines, a firm can offer few first class seats at highest price, more business class seats at medium prices, and most coach seats at lowest price. He shows that the more competitive the market, the greater the price variance/dispersion is likely to be. His model does not contain a theory for average price levels, and no insights for concentration of idle capacity and its implications for pricing. Combining demand uncertainty with greater demand variance/peak load pricing might represent empirical realities of the lodging market, but even this combination is likely unable to generate our observed relationship between idle capacity concentration and prices (as discussed in the previous paragraph, the peak load pricing is unable to explain this result).

Ghemawat (1987) has an alternative story for how uncertainty and lumpiness might generate idle capacity. If lumpiness and uncertainty are high, firms that over-optimistically add capacity suffer from the “winner’s curse”. This curse increases as number of competitors increases (note however, that it is not clear why number of competitors would increase in the first place if lumpiness is indeed high). In this case, we will get higher realizations of idle capacity concentration, and lower prices given more firms in the market and if firms price to cover fixed costs, the result we obtain from the collusive pricing model. However, as Ghemawat discusses, this result is less likely to happen in growth industries where, which Texas lodging market is, where the innate probability of “winner’s curse” is lower. Therefore, this mechanism appears unlikely to be causing our results too.

We finally turn to other models of collusion that lead to idle capacity and discuss whether they generate similar results to the ones obtained in our model. In Ghemawat’s (1984) model, an increase in demand uncertainty makes pre-emptive capacity holding less worthwhile given its higher cost. However, if the leader firm has less uncertainty or that uncertainty favors the leader firm, the leader firm might still hold pre-emptive capacity. This might be the case in our industry, and might explain high concentration and higher prices (if entry is successfully kept out). But it is harder to obtain a result of higher concentration of idle capacity leading to idle prices.

Fershtman and Pakes (2000) develop a model of collusion with dynamic considerations. Given the latter, firms have an incentive to not spoil the market when an entry happens, but rather accommodate. Therefore, in equilibrium, we might see larger number of firms and higher prices (and higher quality of products) rather than fewer firms and higher price. Although not explicitly discussed in their model, it is possible that to get to this forbearance/accommodation result, it is easier if there are pain of forbearance is spread more evenly over incumbents and therefore end up with more firms hanging on to smaller per-firm idle capacity. This would give us the result of lower idle capacity concentration associated with higher prices.[13]

Smith (1981) offers another theory for high concentration of idle capacity. He terms it supply coordination, and it is when larger firms are more likely to have accurate forecasts of an uncertain future, smaller firms recognize this and rely on the larger firm to be the leader in adding capacity. This is equivalent to tacit collusion in capacity addition. In this case, the equilibrium will have higher concentration of idle capacity and higher prices. If the larger firm does not step in and provide this coordinating role, the probability of miscalculations in capacity expansion increases. The equilibrium has lower concentration of idle capacity and lower prices. Note that our results are the opposite of what would be obtained in this model, thereby ruling out this mechanism as a possible explanation for our results.

Summarizing, it appears unlikely that our results of the positive impact of excess capacity on prices and negative impact of the concentration of excess capacity on prices are driven by non-strategic factors like demand variability, lumpy capacity additions etc. Therefore, we are left with the conclusion of evidence of idle capacity helping to sustain less competitive outcomes in the industry.

6. Conclusion

Using data on the Texas lodging industry, we have measured the impact of market concentration and capacity on the ability of firms to tacitly collude. We find evidence that increasing market concentration increases price and increasing the concentration of market idle capacity decreases price. These relationships are robust to a variety of different demand and pricing equation specifications. These relationships are consistent with a supergame theoretic model where capacity helps in oligopolistic pricing, and do not appear to arise from non-strategic reasons like lumpy capacity, or demand uncertainty, or demand variation alone.

There are at least two related issues to explore regarding capacity in the Texas lodging industry. In our pricing equation, we have controlled for the effect of a change in market capacity on pricing. To extend the analysis, one could examine what effect idle capacity has on entry and exit decisions. This paper considers how capacity decisions influence pricing of firms. Benoit and Krishna (1987) examine the reverse issue, i.e., how pricing threats can help collusion in capacity decisions. Therefore, as a second extension of the paper, it would be instructive to study whether the choice of capacity is influenced by pricing in the market.

[1] While we take capacity choice as given for this purpose of this paper, the theoretical literature on capacity selection, especially as it relates to entry deterrence, is extensive (See Bernheim (1984), Dixit (1980), and Waldman (1991)). Conlin & Kadiyali (2006) addresses the issue of capacity selection in the Texas lodging industry. This paper is different from Conlin and Kadiyali (2006) in the following important way: those results indicate there is greater idle capacity in more concentrated markets and greater investment in idle capacity for firms with a large share of market capacity. As we will see later, this paper that increasing market concentration increases price and increasing the concentration of market idle capacity decreases price. While related, the two phenomena of entry deterrence and collusion do not necessarily imply one another (e.g. entry can occur in industries with collusive prices, and price wars can break out despite successful deterrence). Therefore, the two phenomena of excess capacity- deterrence and excess capacity-collusion merit independent study.

[2] See Harrington (2005) and Levenstein and Suslow (2006) who provide a broad survey of collusion detection methodologies; note these surveys study many routes to collusion, and not just capacity-based ones we examine here.

[3] Some properties are required to report their revenues on a monthly basis.

[4] Smith Travel Resource is a private consulting firm that conducts monthly surveys of lodging properties throughout the United States. The surveys include questions on the property's average daily room rate, occupancy rates and operating expenditures.

[5] Many of the brand affiliations reported by SSI were incorrect. See Conlin (1999) for further details.

[6] Because the dataset does not include information from 1990 and 1998, the properties that enter in 1991 and exit in 1997 cannot be determined.

[7] This Herfindahl index is calculated by first multiplying rooms by days opened for each property and summing over all properties owned by the taxpayer. This number for each taxpayer is then divided by the

total yearly market capacity, multiplied by 100, and then squared. Finally, these squared values are summed across all taxpayers in the market.

[8] This Herfindahl index is calculated in a similar manner as the taxpayer yearly capacity Herfindahl index. Instead of being based on yearly taxpayer capacity, it is calculated using the yearly taxpayer idle capacity.

[9] The demand for a property is likely to change if the property goes from an independent (i.e., not brand affiliated) to a brand, from a brand to an independent, or from one brand to another brand. Besides brand recognition and a central reservation system, the renovation sometimes required to become affiliated with a brand may also increase demand and costs. For those brand affiliated properties that are franchised, franchise fees are normally the second largest accounting costs behind labor. Even for brand affiliated properties that are not franchised, properties often incur substantial costs satisfying the standards established by the brand.

[10] We do include these observations when calculating the Herfindahl indexes and percent idle capacity in the market.

[11] While some industry sources use location-based submarkets in cities (e.g. Wall, et. al. 1985), structural modeling of consumer choice for Texas lodging markets indicates consumers make price-location tradeoffs in choosing hotels (see Venkarataram and Kadiyali, 2005). Therefore, location or distance-based city submarket definitions are likely to be very restrictive. While a city- or county-based definition might be broad, it is robust to errors made in the alternatives (location- and distance-based definitions) of defining consumer choice and hence competitive set too narrowly.

[12] We use capacity rather than quantity when calculating the Herfindahl index because we treat this Herfindahl index as exogenous. This assumption of exogeneity is analogous to much of the existing empirical literature assuming that product location is exogenous. In the lodging industry, capacity is one aspect of product location. The empirical results do not change appreciably if this Herfindahl index is considered endogenous or is calculated based on taxpayer quantity (See Section 5.2).

[13] They discuss how when there are 3 unequal sized firms, the middle firm (not largest, not smallest) has the least incentive to deviate, given this firm will not gain as much as largest firm if predatory pricing pushes out smallest firm, and has less temptation to increase profits relative to the smallest firm by deviating.   Of course, this does not tell us anything about the size of idle capacity, only about the size of the firm

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Table 1

Descriptive Statistics By Year

Variable (averages)	1991	1992	1993	1994	1995	1996	1997
Number of Properties	2669	2686	2721	2778	2806	2884	2891
Average Annual Price	43.93	44.32	45.05	45.66	47.05	48.47	49.69
Average Daily Capacity	85.2	84.9	83.9	83.7	84.1	85.6	88.5
Idle Capacity (percentage)	44.7	43.4	41.6	39.9	39.7	40.3	40.2
Market Capacity attributable to Entering Properties (percentage)		2.29	2.24	3.09	3.43	5.21	4.89
Market Capacity attributable to Exiting Properties (percentage)	1.80	2.08	1.41	1.98	1.34	1.85	
Travel Expenditure (in millions)	1079	1123	1178	1248	1358	1487	1651
Population (in thousands)	692	714	719	740	778	812	862
Per Capita Income (in thousands)	18.7	19.2	19.4	20.2	20.8	21.3	22.1
Retail Wage	17.0	17.0	17.1	17.0	17.2	17.3	17.5
Tax Rate (percentage)	12.08	12.10	12.12	12.28	12.35	12.42	12.94
Construction Wage	22.75	23.28	22.95	23.31	23.51	24.10	24.84
	Herfindahl Index Based on Capacity						
City-Segment	3863	3910	3914	3879	3820	3827	3803
County-Segment	2621	2646	2683	2643	2621	2601	2621
City-Sector	3900	3950	3946	3902	3843	3843	3840
County-Sector	2005	2005	2030	1997	1939	1898	1878
	Herfindahl Index Based on Idle Capacity						
City-Segment	3178	3210	3194	3151	3049	3012	2931
County-Segment	2641	2675	2670	2649	2631	2603	2644
City-Sector	3228	3271	3251	3204	3107	3075	3023
County-Sector	2044	2052	2075	2073	1990	1953	1960

Table 2

Demand and Pricing Estimation

MARKET DEFINITION	City-Segment	County-Segment	City-Sector	County-Sector
Demand Equation:				
Own Price (p_{imt})	-0.6851**	-0.7531**	-0.2793	0.0062
	(0.2342)	(0.2048)	(0.2103)	(0.1653)
County Travel Expenditure ($travex_{mt}$)	0.0036**	0.0032**	0.0042**	0.0040**
	(0.0009)	(0.0009)	(0.0009)	(0.0008)
Tax Rate (tax_{mt})	-0.5305**	-0.4475**	-0.4403**	-0.3150**
	(0.1039)	(0.1034)	(0.1036)	(0.0963)
Average Competitor Price ($pavg_{mt}$)	0.2745	0.4769**	0.3027	0.3487**
	(0.2228)	(0.1943)	(0.1868)	(0.1391)
Property Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Pricing Equation:				
Own Quantity (q_{imt})	-0.0319	0.0047	0.1502**	0.3076**
	(0.0364)	(0.0390)	(0.0415)	(0.0485)
Retail Wage ($retailw_{mt}$)	-0.9024**	-0.9151**	-1.0204**	-0.8720**
	(0.0915)	(0.0867)	(0.0998)	(0.0927)
Herfindahl Index based on taxpayer capacity (HI_{mt})	0.0033**	0.0035**	0.0076**	0.0051**
	(0.0014)	(0.0014)	(0.0019)	(0.0019)
Percent Idle Capacity ($idlecap_{mt}$)	-0.0015	-0.0015	0.0051**	0.0056**
	(0.0018)	(0.0014)	(0.0018)	(0.0015)
Herfindahl Index of Idle Capacity ($HIidle_{mt}$)	-0.0033**	-0.0037**	-0.0073**	-0.0051**
	(0.0014)	(0.0014)	(0.0019)	(0.0019)
Change in Market Capacity ($chmcap_{mt}$)	0.2283	0.2814**	-0.0286	0.2559**
	(0.1471)	(0.1467)	(0.1012)	(0.1184)
Property Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
R-squared				
Equation: Demand	.988	.988	.989	.988
Equation: Supply	.982	.982	.978	.973
Number of Observations	8,305	9,639	9,066	10,147

* Significant at the .10 level; ** Statistically significant at the .05 level., Standard errors are in parentheses