When Green Practices Affect Business Performance: An Investigation into California's Hotel Industry. *

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Abstract

Businesses' choice to become environment-friendly is endogenous, which previous studies did not account for in their empirical specifications. This study corrects for endogeneity and uses a novel dataset for the hotels participating in the GreenLeaders program of TripAdvisor.com to investigate the effects of green practices. With two different models, difference-in-differences and generalized synthetic control, I check whether participation in the GreenLeaders program has any effect on the participating hotels' occupancy rates, room prices, and revenues. The findings show that hotels' locations play a determining role in the effects of participation. I find the participating hotels in resorts and small towns command a price and a revenue premium with no effects on their occupancy rates. Further investigation reveals that the hotels in less popular cities enjoy the most benefit from participating in the GreenLeaders program.

JEL Classification Codes: L15, R33, D22, Q56
Keywords: Green hotels, Hotel performance, Green certification, TripAdvisor, GreenLeaders program.

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1 Introduction

Green initiatives in business practices has been a widely discussed issue in recent years due to growing environmental concerns and consumer awareness. The gradual transformation of consumer behavior and their growing interest in the interaction between business organizations and environment have helped many businesses recognize responsible practices as a strategy to gain competitive advantage (Fernie *et al.*, 2010; Jones *et al.*, 2008). In almost every industry, a considerable number of businesses have undertaken green initiatives in order to act responsibly (Laroche *et al.*, 2001; Trudel and Cotte, 2009). Some of the early researchers in social sciences investigating business benefits of green practices are from the tourism literature (Robinson *et al.*, 2016). In the tourism industry, hotels are reported to be the source of 21% of carbon emission (Han *et al.* 2011). Various studies have investigated green features in the tourism and hospitality industry, and a large section of the studies focuses on consumers' willingness-to-pay and attitude for green attributes in hotels.

The ambiguous evidence on hotels' ability to yield revenue premiums and the presence of anecdotal evidence on increased demand for green hotels warrant further analysis into the impact of green certifications on hotels' performance. This study, therefore, investigates the effect of green practices on business performance in the hotel industry, using the listing of green hotels on TripAdvisor.com. This website categorizes, under its GreenLeaders program, the participating hotels around the world into five levels, such as *Platinum*, *Gold*, *Silver*, *Bronze*, and *GreenPartner,* based on their eco-friendly practices. Using a cross-section of 865 hotels of which 342 are green hotels, this paper investigates whether participation in the GreenLeaders program has any effect on the hotels' performance, and whether there exist any heterogeneous effects of participation. The Key research questions include: Do TripAdvisor's GreenLeaders badges have any impact on participating hotels' occupancy rates (Occ), average daily rates (ADR), and revenue per available room (RevPAR)? Is there any heterogeneity in the effects of participation across badge types? In seeking answers to the research questions, this study differs from the prior research in the following ways. This is, to the best of my knowledge, the first paper that addresses the endogeneity bias arising from hotels' self-selection in obtaining green certifications. Apart from the empirical approach, this paper utilizes a novel dataset from TripAdvisor.com, which makes identification of the impacts of green labels on the hotels' performance more reliable. I discuss this in further details in the Data section.

In the commercial real estate sector, business performance and corporate social responsibility (CSR) are closely associated. Organizations with green agenda are usually willing to pay a premium as tenants of green offices. In the hotel industry, however, there are differences concerning the price premium for green hotels. When it comes to a hotel stay, price plays a crucial role in both the leisure and business travelers (Lockyer, 2005). Hotel leases are also much shorter (i.e., one or more nights) compared to office leases (i.e., 3 to as long as 20 years). As a result, travelers may not appreciate the benefits associated with CSR for the price premium in green hotels. Nonetheless, travelers that tend to stay longer and travel frequently may have some preference for green hotels (Robinson *et al.*, 2016). Some of the recent surveys indicate a growing awareness for green choices among travelers. In March 2017, Booking.com conducted a global survey of 10,000 travelers and found 42% of the respondents considered themselves sustainable travelers. In another study conducted by TripAdvisor, two-thirds of the travelers said they planned to make more environment-friendly choices over the following years. Despite a growing awareness among travelers, the overall performance of the green hotels depends on the market share of such travelers (Robinson *et al.*, 2016).

It is possible that green certifications signal different quality, such as prestige. Griskevicius *et al.*, (2010) argue that patronizing green products can be construed as altruistic, and consumers may use green purchase as a means to signal "status." If so, hotels may obtain green certifications to differentiate themselves from their competitors. Mazzeo (2002) shows that firms enjoy a significant benefit by offering differentiated products. Competition in a market drives down prices, but a firm can be less affected by the competition when its products are differentiated. Hence, differentiation is the optimum product choice behavior. In the hotel industry, as long as consumers gain different levels of utility from diverse product types, a competing hotel can differentiate itself by offering green choice and charge a price higher than marginal cost in equilibrium without losing the whole market share. A green traveler may be inclined to forego the utility related to the higher price if he/she has a strong preference for a green stay or the associated differential quality. The distribution of travelers' preferences over product types offered by the hotels is important. If travelers' preferences are skewed in favor of a product type, the resulting price elasticity for a hotel offering the popular product type may be smaller, and vice versa. The relative product-space locations of competitors also affect the relevant price elasticity. Overall, the hotels' profit-maximizing choices of product space locations will determine the underlying tradeoff between price and market share, in other words, their economic performance.

Although a number of earlier studies suggest travelers show preference for green hotels, the financial implications of such findings are inconclusive (Han *et al.*, 2009; Han and Kim, 2010; Lee *et al.*, 2010; Manaktola and Jauhari, 2007). One reason for this inconclusiveness is the fact that "saying is one thing; doing is another," as pointed out by Bosson *et al.* (2004) and Pager and Quillian (2005). Walsman *et al.* (2014) report a RevPAR premium for the hotels with LEED certifications compared to the non-LEED hotels, but due to limitations in their data, they pointed out the need for further research in this subject.

An early study conducted by Chan and Lam (2002) points out the inadequacy of measures within the hotel industry in dealing with pollutants produced by electricity consumption.

Since then, several international studies laid out the foundation for research on the subject. Rivera (2002) demonstrates that the hotels in Costa Rica experienced a price premium after the adoption of a voluntary environmental program. However, the author points out the limitation of the study due to the use of cross-sectional data, limiting their ability to infer causation. Surveying 349 hotels in Poland and Sweden, Bohdanowicz (2006) reports an emergence of recognition for environmental protection needs. Tarí *et al.* (2010), through analysis of variance and cluster analysis of 301 hotels in Spain, report that environmental practices influence hotels performance. Based on a survey of accommodation managers in Spain, Garay and Font (2012) suggest that CSR is mostly altruistically motivated, and environmental responsiveness is a part of it. However, they recognize competitiveness also plays some role in CSR initiatives. Rahman *et al.* (2012) show that chain hotels are more likely to embrace green initiatives compared to independent hotels. In another study conducted using a sample of Greek hotels, Leonidou *et al.* (2013) show that sufficiency of physical and financial resources determines green marketing strategies. As competition intensifies in the market, such strategies become stronger.

Many studies in the real estate sector investigate the operational and financial premiums of green buildings (Fuerst & McAllister, 2011; Zhang *et al.*, 2017). These studies examine buildings with green certifications like LEED or Energy Star. Some find green buildings enjoy a price premium, including evidence of heterogeneous price premiums in various value categories (Das and Wiley, 2014; Eichholtz, Kok, and Quigley, 2010; Robinson and McAllister, 2015). A few studies find that green buildings experience higher development and operating costs (Miller *et al.* 2010; Kok and Jennen, 2012; Nikodem and Fuers, 2013). Robinson *et al.* (2016), however, argue the significant high occupancy and rental rates must be the reason of price premiums in green buildings. Likewise, Das *et al.* (2011) show green buildings enjoy a notably higher rental rate (2.4%) during down markets, but during up markets, the rates drop significantly. Robinson and Reichert (2015) report that green certifications marginally affect appraisal values. Kok and Jennen (2012) show that buildings in the Netherlands with no energy-performance certifications experience 6.5% lower rental rates.

One common limitation of the previous studies is the presence of endogeneity bias, stemming from self-selection of green certifications by the businesses. Arguably, businesses may choose to obtain green labels because they expect to enjoy a price premium. It is possible that the unobserved factors, only known to the businesses, underpin their expectation. In such case, the price premium cannot be attributed to the green labels, but to the aptness of the businesses' decision to go green. On the contrary, the literature on the effects of green certifications on businesses other than office buildings is limited. Besides, office buildings and hotels operate in different settings. The closest study to this article is the one conducted by Robinson *et al.* (2016) who examined financial impact of LEED and Energy Star certifications on hotel revenues. As the authors pointed out, their econometric techniques suffer endogeneity due to unavailability of the information regarding the exact timing of when a hotel went green. Also, the study does not address the bias associated with self-selection of the hotels' green certifications. Due to the limitations of data, econometric techniques, and a limited number of studies in the existing literature, there seems to be a gap in understanding the effect of green labels on the performance of businesses, in particular hotels. This paper seeks to address the gap.

The subsequent part of this paper provides some background information on the GreenLeaders program. The following section illustrates a theoretical model of product differentiation for green hotels, which is followed by a discussion of data, empirical specifications, and results. The paper then presents some analyses of the findings and concludes.

2 GreenLeaders program

In 2013, TripAdvisor commenced the GreenLeaders program in partnership with U.S. Green Building Council's LEED Certification Program, the United Nations Environment Program, the U.S. Environmental Protection Agency's Energy Star program, and other sustainability experts (TripAdvisor, 2018). Under this program, hotels, bed and breakfasts (B&B), and specialty lodgings are awarded for their commitment to the environment and sustainability. The program is available to all the hotels, B&Bs, and specialty lodgings in the U.S., Canada, and some selected countries in Europe. The program is free of charge. A hotel interested in obtaining a GreenLeaders badge is required to participate in an online survey in order to determine its eligibility.[1] If qualified, the score on the survey determines an appropriate badge level, as shown below. All participating hotels must reapply every year to ensure their continued enrollment in the program and to keep their badges on the TripAdvisor page of their properties. I addition to initial screening for the determination of eligibility, all participating hotels are subject to a set of audits conducted every year by independent sustainability organizations. A participating hotel in the GreenLeaders program receives one of the five types of badges (e.g., Platinum, Gold, Silver, Bronze, and GreenPartner) on its listing, a widget for its official website, and a printed certificate. On TripAdvisor.com, travelers can identify GreenLeaders hotels with different levels of badges in their locations of interest. Travelers can also see the full list of practices by clicking a properties GreenLeader icon on its TripAdvisor page. The different types of GreenLeaders awards a property can receive are as follows:

- *Platinum*: 60 percent or greater score on the *Green Practices* survey.
- *Gold*: 50 percent score on the Green Practices survey.
- *Silver*: 40 percent score on the Green Practices survey.

[1] Click ***here*** to view the survey questionnaire.

- *Bronze*: Meets minimum requirements and achieves a 30% score on the Green Practices survey.
- *GreenPartner*: Meets minimum requirements.

[Insert Figure 1 around here]

Figure 1 shows a search result on TripAdvisor.com for the hotels, including GreenLeaders and non-GreenLeaders, in San Francisco. As illustrated, one can easily identify a GreenLeader hotel by its badge on the hotel image, next to its name. The figure includes four GreenLeaders hotels, including Phoenix Hotel, a Joie de Vivre hotel; Best Western Plus Americania, Carriage Inn, and The Good Hotel.

3 A product differentiation model for green hotels

I this section, I set up a simple version of a product differentiation model (Hotelling, 1929; Dixit, 1979; Vives, 1984; Beath and Katsoulacos, 1991; Anderson *et al.*, 1992; Shy, 1995) to illustrate how going green could impact hotel businesses. Let us assume hotels operate in a vertically differentiated market where all consumers have their hotel located at any point on the [0, 1] interval. There is a continuum of consumers uniformly distributed on the interval [0, 1]. G and H denote two hotels that are located at points g and h $(0 \leq g \leq h \leq 1)$ from the origin, respectively. Let us also assume H represents a green (or a high quality) hotel that signifies higher quality (i.e., status, altruism, or any other quality) and G denotes a non-green (or relatively lower quality) hotel. The utility of a consumer located at point n, $n \in [0, 1]$ and staying in hotel $i, i = G, H$ is defined by

$$U_n(i) \equiv \begin{cases} gn - p_G & i = G \\ hn - p_H & i = H \end{cases}$$

where hotel G and H charge the prices p_G and p_H , respectively.

[Insert Figure 2 around here]

I define a two period game, where hotels choose location in the first period, and then choose price in the second period. Before defining the game, let us solve for a Nash-Bertrand equilibrium in prices, assuming fixed locations.

Let $\hat{n}$ denote a traveler who is indifferent to whether he or she chooses to stay in hotel G or H. Assuming that such a traveler exists, and that the traveler $\hat{n}$ intends to locate anywhere between the two hotels, that is $g \leq \hat{n} \leq h$, the intended location of the indifferent traveler is determined by

$$U_{\hat{n}}(G) = g\hat{n} - p_G = h\hat{n} - p_H = U_{\hat{n}}(H) \tag{1}$$

Thus, the utility of a traveler indexed by $\hat{n}$ from staying in hotel G equals his utility from staying in hotel H. As a result, based on the assumption $g \leq \hat{n} \leq h$, the number of travelers staying in hotel G is $\hat{n}$, whereas the number of travelers staying in in hotel H is (1- $\hat{n}$). Solving for $\hat{n}$ from equation (1) gives

$$\hat{n} = \frac{p_H - p_G}{h - g} \quad \text{and} \quad 1 - \hat{n} = 1 - \frac{p_H - p_G}{h - g}$$

Figure 3 illustrates how $\hat{n}$ is determined. The left side of Figure 3 shows the utility for a traveler intending to locate at any point $0 \leq n \leq 1$ when he stays in hotel G or H, assuming $p_H > p_G$. By definition, a traveler located at $\hat{n}$ derives the same utility from staying in hotel

G as the utility from staying in hotel H. In addition, Figure 3 illustrates that all consumers located on $[0, \hat{n}]$ gain a higher utility from staying in hotel G than from staying in hotel H. Likewise, travelers located on $[\hat{n},\ 1]$ gain a higher utility from staying in hotel H (relatively higher quality) than from staying in hotel G.

[Insert Figure 3 around here]

It should be noted that I assume travelers cannot stay in both hotels, hotel G and H, at the same time. I also assume that travelers with reservation utility of zero would not choose to stay in any hotel. Hence, on the left side of Figure 3, all travelers on $[0,\ m]$ will not stay in any hotel, reducing the market size for hotel A to the interval $[m, \hat{n}]$. It is also clear from the right-hand side of Figure 3 that all travelers choose to stay in the Green hotel (or high-quality hotel), hotel H, when $p_G > p_H$, in other words, the price of the lower quality hotel (hotel G) is higher than the price of the higher quality hotel (hotel H).

In the second period, for given locations of hotels, each hotel takes the price set by its competitor as given and determines its price to maximize its profit. Hotel G and H thus solves:

$$\max_{p_G} \pi_G(g, h, p_G, p_H) = p_G \hat{n} = p_G \left[\frac{p_H - p_G}{h - g}\right] \tag{2}$$

$$\max_{p_H} \pi_H(g, h, p_G, p_H) = p_H(1 - \hat{n}) = p_H \left[1 - \frac{p_H - p_G}{h - g}\right]$$

The quadruple $< g^e, h^e, p_G^e(g, h), p_H^e(g, h) >$ is said to be a vertically differentiated market equilibrium if, in the second period, for given locations of hotels (g and h), $p_G^e(g, h)$ and $p_H^e(g, h)$ represent a Nash equilibrium; and in the first period, given the second-period price functions of locations $p^e_G(g,h)$, $p^e_H(g,h)$, and $\hat{n}(p^e_G(g,h), p^e_H(g,h))$, (g^e, h^e) is a Nash equilibrium in location. This is also a subgame perfect equilibrium in which hotels choose their locations in the first stage after accounting for how their location choices will affect the equilibrium prices in the second period and, thereby, profit levels. In the second period, equilibrium actions of the hotels are functions (not scalars) of all the possible given locations of hotels. Solving equation 2 we get:

$$p^e_G(g,h) = \frac{h-g}{3} \quad \text{and} \quad p^e_H(g,h) = \frac{2(h-g)}{3} \tag{3}$$

Note that both the equilibrium prices surpass marginal cost. Equation 3 gives,

Proposition 1: *A green hotel, providing higher quality products (or services), charges a higher price even if the cost for the non-green hotels is same as the cost of the green hotels.*

Substituting $p^e_G(g,h)$ and $p^e_H(g,h)$ from equation 3 into 2 gives,

$$\pi_G(g,h) = \frac{h-g}{9}$$

$$\pi_H(g,h) = \frac{4(h-g)}{9}$$

$\pi_G(g,h)$ and $\pi_H(g,h)$ above show that hotel G and H benefit more as they move further away from each other. This model can be further extended by allowing more than two hotels in the same market to show that as more hotels choose to locate near hotel B, its ability to charge a higher price diminishes. Hence,

Proposition 2: *A green hotel's ability to charge a higher price diminishes as more green hotels enter the market and choose to locate nearby.*

4 Data

My data come from two primary sources: TripAdvisor and STR, Inc.[2] For 626 different cities in the state of California, I construct a dataset with a cross-section of information on 5,157 hotels. Using information directly available from TripAdvisor.com, I am able to determine each hotel's amenities and GreenLeaders badges. In California, there are 824 hotels that participated in GreenLeaders program as of April 2017. In order to determine when each hotel received a GreenLeaders badge since June 2013 through March 2017, I use a proprietary dataset that has been collected by personally contacting the TripAdvisor authority. Figure 4 illustrates numbers of GreenLeaders hotels by their badge types for the 2013-2016 period.

[Insert Figure 4 around here]

From STR, Inc., I collect performance data for all the hotels in California that report their performance information (i.e., occupancy rate, average daily rate (ADR), and revenue per available room (RevPAR)) to STR in daily frequency. STR defines occupancy as the percentage of available rooms sold during a specified period. Daily occupancy rate is calculated by dividing the number of rooms sold by the total number of rooms available on a given day. ADR is a measure of the average price paid for rooms sold, calculated by dividing total room revenue by the number of rooms sold. Lastly, RevPAR is calculated by dividing total room revenue by the total number of available rooms.[3] $RevPAR$ differs from ADR because $RevPAR$ is affected by the number of unoccupied rooms, while ADR shows only the average price of the sold rooms. Of the 5,157 hotels from TripAdvisor's data, STR receives daily performance reports from 3,267 hotels. Because different hotels started reporting to STR from different dates, not all of the 3,267 hotels have performance data for the same length

[2] STR, Inc. is a U.S. based market research company that tracks supply and demand data for multiple market sectors, including the global hotel industry. STR provides market share analysis for major hotel chains and brands in North America, Europe, Asia Pacific, Middle East, and Africa.

[3] https://www.strglobal.com/resources/glossary

of duration in STR's dataset. Besides, in STR's data, a significant number of hotels have missing observations for several months. As a result, after merging TripAdvisor's data with that of STR, I construct a sample of hotels for which there are no missing observations between the period of February 2011 and June 2017, providing a strongly balanced panel data. I merge the two datasets based on the hotels' addresses and names. At this stage, the sample contains 2,446 hotels including 517 GreenLeaders hotels. Next, I construct a number of clusters of hotels by imposing the following condition. I keep a cluster, containing hotels in the same zip code, if it includes at least one green and one non-green hotel. I drop the clusters and the hotels within each of them that do not meet the above condition.

[Insert Table 1 around here]

My final dataset includes 865 hotels of which 342 are green hotels, including 16 Platinums, 37 Golds, 106 Silvers, 99 Bronzes, and 84 GreenPartners, from 98 cities and 145 zip codes. The sample of hotels in the final data represents 16.8% of total hotels and 41.5% of the green hotels in the state of California. The resulting dataset is a strongly balanced panel data with daily occupancy rate, ADR, and RevPAR for each of the 865 hotels since February 01, 2011 through June 29, 2017. See Table 1 for descriptive statistics.

5 Empirical specification

In order to estimate the effects of participation in the GreenLeaders program, I estimate two different models, difference-in-differences (DID) and generalized synthetic control (GSC), both of which are discussed below.

5.1 Difference-in-differences

5.1.1 Estimation sample

A primary principle of any experimental design is that the treated and control units are chosen randomly. This poses a challenge in this study as the hotels' choice to participate in the GreenLeaders program is not randomized. Instead, the hotels endogenously decide to participate in the program. Without addressing the concern, estimating a simple difference-in-differences model will likely produce biased results. The participating hotels (treated group) might be substantially different from the nonparticipating hotels (control group). I, therefore, limit the analysis within a sample of hotels in which the participating and nonparticipating hotels are similar to each other based on their observable characteristics. I assume if the hotels' observable characteristics are not different from each other, their performance (i.e., Occupancy, ADR, and RevPAR) should be similar. As a result, it does not matter which hotel receives a GreenLeaders badge. Hence, a badge awarded to a hotel would assumably mimic a randomized process. One limitation of the assumption is there might be unobserved hotel characteristics that play a role in the hotels' decision to participate in the program. To address the concern, I use a different empirical specification in the subsequent part. In this section, I use a propensity score matching method, particularly nearest neighbor matching, to select a comparable control hotel for each treated hotel (Becker & Hvide, 2017; Zhang *et al.*, 2017; Ichino *et al.*, 2017). The rationale behind using propensity score matched data is to address the bias arising from self-selection of the participating hotels in the GreenLeaders program. The propensity score refers to the probability of receiving a treatment, which, in this case, is receiving a GreenLeaders badge conditional on pre-treatment characteristics. The idea is to match treated and control units based on an *ex-ante* likelihood of receiving treatment predicted by their pre-treatment characteristics (Rosenbaum and Rubin, 1983). The hotel characteristics presented in Table 2 are the pre-treatment characteristics used in the matching process.

I estimate a probit model of participation in the GreenLeaders program on hotel characteristics to estimate propensity scores for all 865 hotels. Next, I use a nearest-neighbor matching method (without replacement) on the estimated propensity scores to obtain a matched treated and control unit pair. To ensure a good match, I impose a caliper of 0.05 so that any treated unit that does not have a control unit within 0.05 of the propensity score of the treated unit is eliminated. I also impose exact matching on the zip-codes of the hotels to control for the location-specific unobserved time-variant factors that may affect both the green and non-green hotels similarly. The matching process discards 89 participating hotels and 270 nonparticipating hotels, leaving in total 506 (253 matched pairs) of green and non-green hotels.

To check how well the probit model reduces differences between the treated and control units, I estimate median absolute standardized bias (MASB), as shown in equation 5 below, from Rosenbaum and Rubin (1985):

$$\text{MASB} = \frac{100(\bar{x}_{i1} - \bar{x}_{i0})}{\sqrt{\frac{1}{2}(s_{i1}^2 + s_{i0}^2)}} \tag{4}$$

where $\bar{x}_{i1}$ and $\bar{x}_{i0}$ denote means of covariate x_i in the treated and control units, respectively. s_{i1}^2 and s_{i0}^2 denote sample variances of covariate x_i in the treated and control units, respectively. Before matching, the MASB estimate was 28.54, which was reduced to 3.27 after matching. According to Rosenbaum and Rubin (1985), an MASB estimate of 20 is "large". It is, therefore, safe to note that the matching has significantly reduced differences between the treated and control groups.

[Insert Table 2 around here]

Table 2 and Figure 5 illustrate how well the characteristics and propensity scores of control units match that of treated units, respectively, after matching. In Table 2, a comparison of the hotel characteristics between "Before Matching" and "After Matching" shows that, on average, the differences between the treated and control units are reduced after creating matched pairs with propensity scores. For instance, before applying the matching procedure, 92.98% of the participating hotels and 75.1% of the non-participating hotels had multilingual staffs, but after matching, the difference was reduced significantly. Figure 5 illustrates that the matching produces a better control group by reducing differences between treated and control units in terms of their estimated propensity scores. Hence, for each treated unit, the matching produces a control unit with similar pre-treatment characteristics. The process also ensures both the treated and control units in a matching pair are located in the same zip-code. Figure 6 shows the differences in occupancy rates, ADR, and RevPAR between treated and control units have reduced after the matching procedure.

[Insert Figure 5 around here]

[Insert Figure 6 around here]

5.1.2 Estimation

In order to estimate the effect of participation on the three outcome variables (i.e., *Occupancy*, *ADR* and *RevPAR*), I estimate the regression represented by equation 6 with a zip-code fixed effect. I estimate the regression three times for each of the outcome variables.

$$Y_{itz} = \beta_0 + \beta_1 Treated_{iz} + \beta_2 Post_{itz} + \beta_3 Post_{itz} * Treated_{iz} + \gamma X_{iz} + \sum_{t=2}^{T} \beta_t month_t + \sum_{k=2}^{K} \beta_k year_k + \sum_{d=2}^{D} \beta_d day_d + \epsilon_{itz} \quad (5)$$

In equation 5, the outcome variable Y_{itz} denotes *Occupancy rate, or ADR, or RevPAR for* hotel i in time period t, and in zip-code z. The variable *Post* takes a value of 1 when the observation is in the post-treatment period. *Treated* is a dummy variable if the observation participates in the GreenLeaders program, γ is the coefficient of time-invariant hotel characteristic X; *month*, *year* and *day* denote dummy variables for month, year, and each day of a given week; and ϵ denotes residuals. The coefficient of interest β_3 indicates the effect of participation on Occupancy, ADR, and RevPAR. In addition, β_1 is a coefficient of interest as it indicates pre-treatment effects. β_1 is also a good indicator of the effectiveness of the propensity score matching in reducing differences between the treated and control units. A statistically insignificant β_1 will signify that, on average, the treated and control units are not substantially different from each other in terms of their outcome variables. In order to analyze further, I extend the model in several ways in a subsequent part. I examine potential heterogeneous effects of participation in the GreenLeaders program across badges (i.e., *Platinum, Gold, Silver, Bronze,* and *GreenPartner*) and types of locations (i.e., interstate, resort, small metro/town, suburban, and urban).

5.2 Generalized synthetic control

There may be concerns as to the estimated participation effect using the DID model with propensity score matched data. The presence of unobserved time-varying confounders can bias the DID estimates. For example, some hotels might have improved their quality over time and eventually opted in for green certifications to signal better quality. Unobserved and time-variant changes of such nature, if not taken into account, can confound the DID estimates. Because propensity score matching only reduces observable hotel differences, unobservable and potentially time-varying hotel characteristics are left unaddressed in the DID model. To address the concern and to complement the DID results, I use a generalized synthetic control (GSC) method proposed by Xu (2017). The model allows estimation of the treatment effect on the treated for multiple treated groups with multiple treatment periods. In principle, this model is analogous to the synthetic control method proposed by Abadie *et al.* (2010) as it essentially reweights the pretreatment treated outcomes for benchmarking while choosing weights for control units and utilizes cross-sectional correlations between treated and control units in order to predict counterfactuals. However, unlike synthetic control method, this method uses a dimension reduction procedure before reweighting so that the vectors to be reweighted on are smoothed across control units.

5.2.1 Model Framework

To illustrate the model framework, I adopt the same notations as Xu (2017). Let Y_{it} denote the outcome of interest for unit (i.e., hotel) i at time t. $\mathcal{T}$ and $\mathcal{C}$ denote the sets of units in treated and control groups, respectively. The total number of units is represented by $N = N_{tr} + N_{co}$ in which N_{tr} and N_{co} indicate the numbers of treated and control units, respectively. All units are observed for T periods, from time 1 to time T. Let $T_{0,i}$ denote the number of pre-treatment periods for unit i that is first exposed to the treatment (i.e., enters the GreenLeaders program) at time $(T_{0,i} + 1)$ and later observed for $q_i = T - T_{0,i}$ periods. Over the observed time span, control units are never exposed to the treatment. For notational convenience, let us assume that all the treated units are first exposed to the treatment at the same time, i.e., $T_{0,i} = T_0$ and $q_i = q$; variable treatment periods can also be accommodated. Firstly, the model assumes Y_{it} is given by a linear factor model:

$$Y_{it} = \delta_{it} D_{it} + x_{it}' \beta + \lambda_i' f_t + \varepsilon_{it},$$

where D_{it} denotes the treatment indicator that takes a value of 1 if unit i has been exposed to the treatment prior to time t, or else 0 (i.e., $D_{it} = 1$ when$i \in \mathcal{T}$ and $t > \mathcal{T}_0$, or else $D_{it} = 0$). δ_{it} denotes the heterogeneous treatment effect on unit i at time t; x_{it} represents the observed covariate(s), β denotes a vector of unknown parameters, f_t denotes a vector of unobserved common factors, λ_i denotes a vector of unknown factor loadings, and ε_{it} denotes unobserved idiosyncratic error terms for unit i at time t and has a mean value of zero.[4] Let $Y_{it}(1)$ and $Y_{it}(0)$ be the potential outcomes for individual i at time t when $D_{it} = 1$ or $D_{it} = 0$, respectively. Hence, we obtain $Y_{it}(0) = x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it}$, and $Y_{it}(1) = \delta_{it} + x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it}$. We can derive the individual treatment effect on the treated unit i at time t as $\delta_{it} = Y_{it}(1) - Y_{it}(0)$ for $i \in \mathcal{T}$, and $t > T_0$. The key estimate of interest, average treatment effect on the treated (ATT) at time t (when $t > T_0$):

$$ATT_{t,t>T_0} = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} [Y_{it}(1) - Y_{it}(0)] = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} \delta_{it}$$

5.2.2 Estimation strategy

In the first stage, a GSC estimator is estimated for each treated unit's treatment effect. This is, in essence, based on Bai (2009)'s out-of-sample prediction method. For the treatment effect on treated unit i at time period t, the GSC estimator is given by the difference between an actual outcome and its estimated counterfactual as follows: $\hat{\delta}_{it} = Y_{it}(1) - \hat{Y}_{it}(0)$, whereas $\hat{Y}_{it}(0)$ is estimated in three steps. The first step involves estimation of IFE model using only control units information to obtain $\hat{F}$, $\hat{\Lambda}_{co}$, and $\hat{\beta}$:

$$\text{Step 1: } (\hat{F}, \hat{\Lambda}_{co}, \hat{\beta}) = \underset{\tilde{\beta}, \tilde{F}, \tilde{\Lambda}_{co}}{\text{argmin}} \sum_{i \in C} (Y_i - X_i \tilde{\beta} - \tilde{F}\tilde{\lambda}_i)'(Y_i - X_i \tilde{\beta} - \tilde{F}\tilde{\lambda}_i)$$

$$s.t. \ \tilde{F}'\tilde{F}/T = I_r \text{ and } \tilde{\Lambda}'_{co}\tilde{\Lambda}_{co} = \text{diagonal}.$$

The second step involves estimation of factor loadings for each treated unit by minimizing the mean squared error of the predicted treated outcome in pre-treatment periods:

[4] In interactive fixed effects (IFE) model proposed by Bai (2009), the time varying coefficients are referred to as common factors or latent factors and the unit-specific intercepts are known as factor loadings.

$$\text{step 2: } \hat{\lambda}_i = \underset{\hat{\lambda}_i}{\text{argmin}} \ (Y_i^0 - X_i^0\hat{\beta} - \hat{F}^0\tilde{\lambda}_i)'(Y_i^0 - X_i^0\hat{\beta} - \hat{F}^0\tilde{\lambda}_i)$$

$$= (\hat{F^0}'\hat{F^0})^{-1}\hat{F^0}'(Y_i^0 - X_i^0\hat{\beta}), \ i \in \mathcal{T},$$

where $\hat{\beta}$ and $\hat{F}^0$ are estimated in step 1, and the superscript "0" indicates pre-treatment period. In the next step, treated counterfactuals are estimated based on $\hat{\beta}$, $\hat{F}$, and $\hat{\lambda}_i$.

$$\text{Step 3: } \hat{Y}_{it}(0) = x_{it}'\hat{\beta} + \hat{\lambda}_i'\hat{f}_t \ , \ i \in \mathcal{T} \ , \ t > \mathcal{T}$$

Hence, the estimator for ATT_t *is:*

$$\widehat{ATT}_t = (1/N_{tr})\sum_{i\in\mathcal{T}}[Y_{it}(1) - \hat{Y}_{it}(0)] \ \mathit{for} \ t > T_0$$

Before estimating causal effect, a cross-validation procedure is used - in case of limited knowledge on the number of factors to be included - to select the right model. This procedure relies on both the treated and control group information in the pre-treatment periods.[5] The idea is to hold back a small portion of data (i.e., treated group's one pre-treatment period) and utilize the remaining data in order to predict the held-back data. The next step is to then select the model that makes the most accurate predictions on average.

To obtain uncertainty estimates of the estimator, GSC uses a parametric bootstrap procedure. Conditional on observed covariates, unobserved factors, and factor loadings, the model provides uncertainty estimates using a parametric bootstrap procedure by resampling the residuals. The goal is to estimate the conditional variance of ATT estimator (i.e., $\text{VAR}_\varepsilon(\widehat{ATT}|D, X, \Lambda, F)$. The residuals, ε_i, represent the only random variable that is not

[5] See Xu (2017) for further details on the cross-validation procedure.

being conditioned on because they are assumed to be independent of the treatment assignment, factors, factor loadings, and observed covariates. The model treats ε_i as measurement errors that cannot be explained, but are unrelated to the treatment assignments.

The parametric bootstrap procedure simulates treated counterfactuals and control units based on the following resampling procedure:

$$
\begin{aligned}
\tilde{Y}_i(0) &= X_i\hat{\beta} + \hat{F}\hat{\lambda}_i + \tilde{\varepsilon}_i, \forall i \in \mathcal{C}; \\
\tilde{Y}_i(0) &= X_i\hat{\beta} + \hat{F}\hat{\lambda}_i + \tilde{\varepsilon}_i^p, \forall i \in \mathcal{T},
\end{aligned}
$$

where $\tilde{Y}_i(0)$ denotes a vector of simulated outcomes in the absence of treatment; $X_i\hat{\beta} + \hat{F}\hat{\lambda}_i$ provides the estimated conditional mean; and $\tilde{\varepsilon}_i$ and $\tilde{\varepsilon}_i^p$ represent resampled residuals for unit i, which either belongs to treated or control group. As $\hat{F}$ and $\hat{\beta}$ are estimated based on control group data, $X_i\hat{\beta} + \hat{F}\hat{\lambda}_i$ fits $X_i\beta + F\lambda_i$ better for control units than treated units. As a result, $\tilde{\varepsilon}_i^p$ has a greater variance compared to $\tilde{\varepsilon}_i$. Thus $\tilde{\varepsilon}_i$ and $\tilde{\varepsilon}_i^p$ are drawn from disparate empirical distributions. $\tilde{\varepsilon}_i$ is drawn from the empirical distribution of the residuals of IFE model, whereas $\tilde{\varepsilon}_i^p$ is the prediction error of IFE model for treated counterfactuals. Incorporating control group information, GSC uses a cross-validation procedure to simulate $\tilde{\varepsilon}_i^p$. The model is based on the following assumptions: (1) the residuals are independent and homoskedastic across space; and (2) the treated and control groups follow the same factor model (Efron 2012; Xu 2017).

6 Results

6.1 Participation effect

[Insert Table 3 around here]

Table 3 presents the DID and the GSC estimates in panel A and B, respectively. Each column shows results for different regressions: column 1, 2, and 3 present results for the regressions with dependent variables *Occupancy*, *ADR,* and *RevPAR*, respectively. Under panel A, I find none of the coefficients for *Treated* and *Post* are statistically significant. It is important to note here that the coefficients for *Treated* also indicate the effectiveness of the propensity score matching in reducing differences between the green and non-green hotels. Because none of the coefficients for *Occupancy*, *ADR,* and *RevPAR* are statistically significant, I can infer that the treated and control groups are not statistically different from each other, in terms of their observable characteristics as well as the dependent variables. The coefficient of interest (β_3) for *Post*Treated* is significant for RevPAR at 10% level. This implies after participation in GreenLeaders program, the participating hotels (treated group) experience an increase of $2.82 in their RevPAR relative to the non-participating hotels (control group). Participation does not appear to have any statistically significant effect on *Occupancy* and *ADR*. Some of the other minor interesting results from the DID model include the hotels with *Babysitting* services charge $92.299 higher price, resulting in $63.576 higher *RevPAR* relative to their counterparts. *Babysitting* services are perhaps highly correlated with unobserved hotel qualities that help them enjoy a substantial price premium. Likewise, hotels with *Business center* charge on average $12.43 more than others, and hotels with *Breakfast included* services experience a 2.23 percent higher occupancy rate with no statistically significant change in ADR and RevPAR. On the contrary, based on the estimates from GSC model, presented under panel B, I find participation has no effects on the participating hotels' *Occupancy*, *ADR,* and *RevPAR.*

My presented results provide average treatment effects across all hotels. Perhaps the treatment effect differs based on types of GreenLeaders badges, locations, and so forth. In the subsequent part, I estimate the effects of participation in the GreenLeaders program in several ways. At first, I investigate the potential heterogeneous effects of participation in the

GreenLeaders program across the hotels' badges types. Next, I examine whether location plays any role in the effect of participation.

6.2 Heterogeneous participation effects across badge types

[Insert Table 4 around here]

To investigate potential heterogeneous effects across different badges of the GreenLeaders hotels, I estimate both the DID and GSC models. In Table 4, column 1 to 6 report coefficients of the participation effects by badge types. Column 1 to 3 report results from the DID model, and column 4 to 6 report results from the GSC model. Column 7, 8, and 9 report numbers of the treated units, control units, and total observations for the GSC estimates. Using DID, I find only *Gold* and *GreenPartner* have statistically significant effects on both *ADR* and *RevPAR* of the participating hotels. However, *Occupancy* of the participating hotels is unaffected. With the GSC model, on the contrary, I do not find any of the badges having a statistically significant effect on *Occupancy, ADR,* and *RevPAR* of the participating hotels.

6.3 Participation effects across location types

All the hotels in my dataset can be categorized into six different types of locations, such as resort, small/metro town, airport, suburban, urban, and interstate. I examine if participation in the GreenLeaders program affects the participating hotels differently across location types. See Table 7 for definitions of the location segments. Table 5 reports results for the DID and GSC models under panel A and B, respectively, by the hotels' location types. Panel A illustrates results for the three dependent variables, Occupancy, ADR, RevPAR. Each of the variables has been regressed separately by the six location types. The results clearly indicate the effect of the participation in GreenLeaders program varies depending on the hotels' location types. Although *Occupancy* rates of the hotels are not affected, participating hotels located in *Resort* and *Small/metro town* do see an average increase of \$14.669 and \$9.075 in their *ADR,* respectively. Because the *Occupancy* rate is unaffected, an increase in *ADR* should increase a hotel's *RevPAR*, and this is what I find. Looking at RevPAR, we see the hotels within *Resort* and *Small/metro town* experience \$10.016 and \$6.165 increase on average, respectively. None of the participating hotels in other location types has any statistically significant change in their *Occupancy, ADR,* and *RevPAR.*

[Insert Table 5 around here]

The results of the GSC model, presented in panel B of Table 5, show similar effects of participation as found using the DID model. However, GSC model estimates indicate the magnitudes of the participation effects are relatively less. Based on this model, the participating hotels in *Resort* and *Small/metro town* experience \$8.716 and \$3.367 average increase in ADR, respectively. As a result, the RevPAR increases by \$6.061 and \$3.387, respectively. The *Occupancy* rates are unaffected. Again, I do not find any effect of participation for the hotels in other location types. Overall, the results presented in Table 5 illustrate locations play an essential role in determining the effect of participation in the GreenLeaders program.

7 Discussion

Why do we see a price premium in some GreenLeaders hotels? The theoretical framework illustrated above explains why and how green hotels could potentially differentiate themselves. In essence, by differentiating, a hotel does not have to compete as directly with its rivals. Because of less competition, the hotel can then command a price premium without any significant loss of market share, given that there is sufficient demand for the product in the market. It is important to note here that the increase in ADR of the GreenLeaders hotels does not necessarily mean the hotels charge a higher price, although it is possible.

Another explanation may be the participating hotels within *Resort* and *Small/metro town* are able to sell more premium rooms after participation in the program. The price premium in the participating hotels have two possible implications: (1) the participating hotels do not attract any new segment of customers, but some customers are willing to pay more when they recognize the hotels as green hotels. However, according to the economic principles of supply and demand, an increase in price should result in a decreased demand. This means the price premium in the participating hotels should cause a drop in their occupancy rate, which I do not find to be the case. Hence, the first implication seems to be less plausible. (2) Another possibility is the participating hotels are able to differentiate themselves in a way that they can draw a new segment of customers who are less price sensitive and, hence, are likely more interested in premium rooms. In this case, any decrease in occupancy rate due to the price premium may be compensated by the new segment of less price sensitive customers. As a result, overall occupancy does not change significantly in the participating hotels. Table 5 results lend credence to the second implication. An important aspect of the results is that the GSC estimates appear to be always conservative compared to the DID estimates. Hence, the actual effect of participation can be within a range in which the DID and GSC estimates provide upper and lower bounds, respectively, of the true participation effect.

A survey conducted by TripAdvisor reports almost 25% of Americans are consciously trying to make eco-friendly choices when it comes to their hotel stays (Harrison, 2014). Despite quite a few anecdotal evidence showing an increasing demand for green choices among travelers, why do the green hotels in only *Resort* and *Small/metro town* types of locations have higher *ADR* and *RevPAR*? Why not other location types? One possible explanation may be the market dynamics in different locations. Because small-town and resort hotels are mostly driven by leisure travelers who tend to stay longer, their hotel choice decisions are likely more conscious and careful. As a result, they could be more interested in green hotels. On the other hand, big-city, airport, interstate, and suburban hotels attract business and other kinds of travelers whose average length of stay is relatively shorter than leisure travelers. It is also possible that majority of these travelers are under strict time constraints, making it costly for them to search and stay in green hotels. Besides, a lot of business travelers have to follow their employers' travel policy for reimbursement of the travel expenses. Consequently, a business traveler may not be able to stay in a green hotel of his or her choice.

[Insert Table 6 around here]

Further investigation into the TripAdvisor's city-popularity-rank reveals most of the hotels from *Resorts* and *Small/metro Towns* in my data are from less popular cities. Unlike hotels in small cities, hotels in big or more popular cities engage in various marketing and promotional activities in order to differentiate themselves and stay ahead of the competition (Sharkey 2013). It is possible that these marketing and promotional activities - which are less intense in small cities - distort the hotel choice decisions of big-city travelers who would otherwise patronize a green hotel without hesitation. Besides, hotel prices vary considerably depending on the popularity of a city. For instance, a Courtyard by Marriott standard room in Tampa costs approximately $109 on a regular weekend, whereas in a relatively more popular city, such as the New York City, the same kind of room on the same weekend may cost as much as $409.[6] As a result, a customer who is relatively less price sensitive in a small (or less expensive) city may become very price sensitive in a big (or more expensive) city to be able to pay more for staying in a green hotel. All of these may result in the green hotels in big cities having no statistically significant impact on their economic outcomes (i.e., *Occupancy*, *ADR,* and *RevPAR*) when they participate in GreenLeaders program.

The results from Table 6 supports my findings from Table 5. Table 6 reports the coefficients of $Post_{itz} * Treated_{iz}$ from the DID model represented by equation 6. As I move from column

[6] Based on search results on TripAdvisor.com on December 10, 2017.

1 to column 7, I estimate the DID model with the matched data by incrementally excluding more cities (thereby, the hotels located within) from the top of the city-popularity-rank by TripAdvisor. Column 1 excludes no cities and Column 7 excludes 60 cities. One interesting finding in Table 6 is as we move from column 1 to 7 along the ADR and RevPAR rows, we see the coefficients become gradually larger, although not all of them are statistically significant. This phenomenon is absent when *Occupancy* is the dependent variable. For *ADR*, I find statistically significant results when top 50 or greater number of most popular cities are excluded. However, for RevPAR, I find statistically significant participation effect when no cities and 40 or greater number of most popular cities are excluded. These results bolster my earlier findings and imply the hotels in less popular cities enjoy the most benefits from participating in the GreenLeaders program. As we move down the TripAdvisor's city-popularity-rank, participation effects on the GreenLeaders hotels' ADR and RevPAR increase in terms of statistical significance as well as magnitude.

8 Conclusion

Overall, this paper investigates the effect of participation in TripAdvisor's GreenLeaders program by investigating the hotels in California. In particular, using two different models, difference-in-differences and generalized synthetic control, I have examined whether participation in GreenLeaders program has any effect on the participating hotels' occupancy rates, average daily rates (ADR) and revenue per available room (RevPAR). My findings show that the effects of participation depend on the location of a hotel. Based on the full sample of hotels, on average, participation in the GreenLeaders program does not affect the hotels' performance. However, analyses on the hotels by their location types reveal that the hotels located in resorts and small/metro cities see increases in their ADR and RevPAR. Further analysis based on TripAdvisor's city-popularity-rank reveals that hotels in less popular cities get the most benefit from participating in the GreenLeaders program. This supports the participation effects found in hotels within *Resort* and *Small/metro town* types location because all the hotels in my data from within these two types of locations are predominantly located in less popular cities.

I argue the degree of competition across location types may explain the results. Green hotels can signal better quality, higher prestige, altruism, and so forth. Hence, hotels may go green in order to differentiate from competitors. But the effect of differentiation depends on how closely other hotels are located in the product space. In big cities, competition is intense. As more hotels try to differentiate themselves to stay ahead of their competitors, they end up locating close to each other in the product space, undercutting each other's market share. Conversely, in less popular cities, due to relatively less competition, GreenLeaders hotels can differentiate themselves sufficiently to have a statistically significant effect on their performance. Besides, price sensitivity of a customer could play an important role here. A traveler who is relatively less price sensitive in a small town may be highly price sensitive in a popular city because of the substantial price differences between the two locations. For a traveler, when the prices are too high, the utility gain from staying in a green hotel may be much less than the disutility from paying the associated high price premium in a popular city. As a result, a green hotel in a popular city may be a less desirable option for the traveler. The results of this study thus point out to the need for asking when going green pays off instead of whether going green pays off.

One limitation of this paper is the absence of an analysis into how prices and number of online bookings in TripAdvisor.com changed for the GreenLeaders hotels after receiving their badges. As travelers can conveniently search for green hotels on TripAdvisor.com, an analysis with the prices and online booking data directly from the website could provide more accurate results on the effect of participation. Due to unavailability of online booking and price data, such analysis was not possible. Also, a caveat for explaining the results of this study is that the increase in ADR and RevPAR within green hotels does not imply an increase in profitability. This study could not estimate the effect of participation on hotels' profitability due to unavailability of cost data. Although some hotels might have undergone operational changes requiring additional initial investment for becoming green, arguably, their lower operating costs from, say, energy savings could compensate for the initial investment and eventually increase profitability. In the GreenLeaders program, the minimum requirement for a GreenPartner badge is incorporation of initiatives like linen and bath towel reuse program from which hotels can save a significant amount of cost associated with energy, water, detergent, labor, and linen or towel replacement (Werntz, 2015). Yet, without cost data, it is impossible to objectively determine the effect of participation on the hotels' profitability. On the contrary, in addition to TripAdvisor's GreenLeaders program, there are a number of other green certification programs that evolved over the past few years. This study does not take into account if a participating hotel has other green certifications. It is also possible that a hotel with no GreenLeaders badge has certification(s) from other program(s). However, with more than 11,000 participants from around the world and almost 6,000 hotels from within the U.S., TripAdvisor's GreenLeaders program is claimed to be the largest green certification program in the hotel industry (Hasek, 2016). Also, the program's collaboration with globally reputed organizations, such as LEED, Energy Star, and UNEP, lends credibility to the authenticity of the program. Nonetheless, the limitations of this study offer opportunities for future research.

This paper makes several contributions to the literature of green certifications and business performance. To the best of my knowledge, this is the first paper that corrects for endogeneity, stemming from businesses' self-selection of green certifications, and estimates causal effects of green certifications on the performance of green hotels. Alongside offering statistical evidence on the role of locations in gaining economic benefits from green certifications, this study presents different perspectives on how and when going green could pay off. For businesses, this paper shows economic benefits of going green and provides managerial insights into when going green could work as a strategy to differentiate in a competitive market.

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Table 1: Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
Occupancy	73.28	23.06	0	100
ADR	132.76	77.67	0	2314.82
RevPAR	101.91	74.84	0	2245.43
Platinum	0.02	0.13	0	1
Gold	0.04	0.2	0	1
Silver	0.12	0.33	0	1
Bronze	0.11	0.32	0	1
Green Partner	0.10	0.31	0	1
Banquet room	0.44	0.49	0	1
Babysitting facility	0.05	0.22	0	1
Airport transport	0.21	0.41	0	1
Breakfast included	0.49	0.5	0	1
Free parking	0.57	0.5	0	1
Fitness center	0.71	0.45	0	1
Business center	0.77	0.42	0	1
Multilingual staffs	0.82	0.38	0	1
Conference facility	0.46	0.5	0	1
Meeting room	0.69	0.46	0	1
Franchise	0.59	0.49	0	1
Chain	0.27	0.44	0	1
Independent	0.14	0.35	0	1
Luxury	0.16	0.37	0	1
Upscale	0.2	0.4	0	1
Mid-price	0.34	0.48	0	1
Economy	0.18	0.39	0	1
Budget	0.11	0.32	0	1
Resort	0.17	0.37	0	1
Small/metro town	0.08	0.27	0	1
Airport	0.12	0.32	0	1
Suburb	0.38	0.49	0	1
Urban	0.21	0.41	0	1
Interstate	0.04	0.19	0	1
City popularity rank	59.51	84.07	1	527

Notes: This table reports descriptive statistics for all the dependent variables, such as Occupancy rate *(Occupancy)*, Average Daily Rate *(ADR)*, and Revenue Per Available Room *(RevPAR)*, and independent variables for 865 hotels in the state of California. The dependent variables are in daily frequency, which span a period since February 01, 2011 through June 29, 2017, whereas all the independent variables are dummy variables. There are five different types of independent variables reported in this table. Variables related to GreenLeaders badges (i.e., *Platinum, Gold, Silver, Bronze,* and *GreenPartner*), hotel amenities (i.e., *Banquet room, Babysitting facility, Airport transport, Breakfast included, Free parking, Fitness center, Business center, Multilingual staffs, Conference facility,* and *Meeting room*), chain affiliation (i.e., *Franchise, Chain,* and *Independent*), hotel class (i.e., *Luxury, Upscale, Mid-price, Economy,* and *Budget*), and hotel location (i.e., *Resort, Small/metro town, Airport, Suburb, Urban, Interstate,* and *City popularity rank*)

Table 2: Summary of covariates' balance before and after matching

	Before Matching		After Matching	
Variables: hotel characteristics	Participating Hotels	Non-participating Hotels	Participating Hotels	Non-Participating Hotels
Multilingual Staff	0.9298	0.751	0.9224	0.9353
Conference Facility	0.652	0.3314	0.5776	0.5647
Meeting Room	0.8684	0.5728	0.8362	0.8491
Franchise	0.5292	0.6322	0.6293	0.6379
Chain	0.3304	0.228	0.2155	0.2026
Independent	0.1404	0.1398	0.1552	0.1595
Luxury	0.2485	0.0996	0.1552	0.1638
Upscale	0.2865	0.1456	0.25	0.2457
Mid-price	0.3421	0.3467	0.444	0.431
Economy	0.1111	0.2261	0.1336	0.1422
Budget	0.0117	0.182	0.0172	0.0172

Notes: This table illustrates how well the characteristics of the GreenLeaders hotels (treatment units) matched that of non-GreenLeaders (control units) hotels after matching the former with the latter based on propensity score matching. In particular, I use a nearest-neighbor matching method (without replacement) to obtain a matched treatment and control unit pair. To ensure a good match, I impose a caliper of 0.05 so that any treatment unit that does not have a control unit within 0.05 of the propensity score of the treatment unit is eliminated. A comparison of the hotel characteristics between "Before Matching" and "After Matching" shows that, on average, the differences between the treatment and control units are reduced after creating matched pairs with propensity scores.

Table 3: Participation effect in the GreenLeaders program: DID estimates with matched data vs. GSC

Covariates	Occupancy (1)	ADR (2)	RevPAR (3)
	Panel A: DID		
Treated	1.145	-0.724	0.933
	(0.724)	(3.104)	(2.446)
Post	0.107	0.287	0.049
	(0.480)	(1.401)	(1.288)
Post*Treated	-0.426	2.952	2.819*
	(0.621)	(1.886)	(1.465)
Banquet room	-0.646	7.488	7.397*
	(1.309)	(5.852)	(4.432)
Babysitting	-3.025*	92.299***	63.576***
	(1.735)	(19.738)	(13.383)
Airport transportation	0.345	9.351	6.966
	(1.584)	(10.761)	(8.246)
Breakfast included	2.776**	1.161	3.955
	(1.395)	(3.889)	(3.223)
Free parking	0.003	7.835	5.201
	(1.428)	(8.182)	(5.752)
Fitness center	1.167	3.495	3.081
	(1.954)	(6.222)	(4.681)
Business center	1.907	12.434**	6.503
	(2.181)	(5.999)	(4.784)
Multilingual staff	-0.761	4.958	3.755
	(2.451)	(5.392)	(4.837)
Conference facility	1.035	8.574	6.024
	(1.523)	(6.578)	(5.204)
Meeting room	2.446	12.158	9.220
	(2.195)	(7.597)	(6.303)
Zip-code fixed effect	Yes	Yes	Yes
Observation	1,189,228	1,189,228	1,189,228
R^2	0.1760	0.2749	0.4991
	Panel B: GSC		
Participation	-0.002	0.062	1.61
	(0.9255)	(1.43)	(1.235)
Observation	2,024,965	2,024,965	2,024,965
Treated	342	342	342
Control	523	523	523

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parenthesis; and standard errors reported under panel A are robust at the zip-code level. This table presents estimates for the effects of participation in the GreenLeaders program based on two different models, Difference in Differences (DID) and Generalized Synthetic Control (GSC) under panel A and B, respectively. The results report whether participation has any effect on the hotels' *Occupancy, ADR,* and *RevPAR*. Each column shows results for different regressions: columns 1, 2, and 3 present results for the regressions with dependent variables *Occupancy*, *ADR,* and *RevPAR*, respectively.

Table 4: Heterogeneous effects across badges

	DID			GSC					
Covariates: Badges	Occupancy	ADR	RevPAR	Occupancy	ADR	RevPAR	Treatment Units	Control Units	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Platinum	-1.302	-1.333	-0.448	-3.725	-0.236	-7.596	14	523	1,257,117
	(2.186)	(3.564)	(3.731)	(2.301)	(4.220)	(5.083)			
Gold	-1.770	6.652*	6.645*	-2.531	1.148	-6.918	36	523	1,308,619
	(1.414)	(4.002)	(3.724)	(1.516)	(2.431)	(3.863)			
Silver	0.0153	-1.296	-0.716	-0.332	2.432	-6.666	104	523	1,467,807
	(0.865)	(2.010)	(1.780)	(0.859)	(2.015)	(2.890)			
Bronze	0.924	2.206	1.452	0.362	-0.235	-3.227	98	523	1,453,761
	(0.856)	(2.799)	(2.399)	(0.872)	(1.498)	(1.95)			
Green-Partner	-1.975	7.760**	7.554***	-1.102	1.477	-1.294	90	523	1,435,033
	(1.909)	(3.001)	(2.484)	(0.950)	(1.561)	(2.06)			
Number of Hotels	506	506	506						
N	1189228	1189228	1189228						
R^2	0.1735	0.4666	0.6070						

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parenthesis; and standard errors reported under panel DID are robust at the zip-code level. This table reports estimates for the potential heterogeneous effects across different badges of the GreenLeaders hotels using both the difference-in-differences (DID) and generalized synthetic control (GSC) models. Column 1 to 6 report coefficients of the participation effects by badge types. Column 1 to 3 report results from the DID model, and column 4 to 6 report results from the GSC model. Column 7, 8, and 9 report, respectively, the numbers of treated units, control units, and total observations for the GSC estimates.

Table 5: GreenLeaders' participation by location types

Dependent variables	Resort	Small/metro town	Airport	Suburban	Urban	Interstate
			Panel A: DID			
Occupancy	-0.335	0.080	-1.018	-1.061	-0.535	2.669
	(0.857)	(0.969)	(0.546)	(0.955)	(1.291)	(3.289)
ADR	14.669***	9.075**	-1.225	-0.234	-0.117	4.994
	(4.529)	(4.225)	(0.636)	(3.462)	(3.552)	(7.984)
RevPAR	10.016**	6.165**	-2.388	0.153	-1.115	8.061
	(4.324)	(2.969)	(0.441)	(2.871)	(3.538)	(7.770)
Zip code fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	177,916	88,958	168,552	496,292	234,100	23,410
Number of hotels	76	38	72	210	100	10
			Panel B: GSC			
Occupancy	-0.723	2.268	-2.056	-0.851	0.981	4.081
	(1.334)	(2.236)	(2.405)	(1.154)	(1.537)	(3.551)
ADR	8.716**	3.367**	3.208	1.614	-1.232	2.415
	(3.214)	(1.238)	(2.292)	(1.417)	(3.338)	(1.705)
RevPAR	6.061**	3.387**	0.4738	-0.2169	-1.803	2.627
	(2.71)	(1.261)	(3.392)	(1.295)	(3.762)	(2.769)
Unobserved factors	5	5	5	5	5	5
N	341786	159188	241123	777212	430744	74912
Treated hotels	50	19	38	135	91	7
Control hotels	96	49	65	197	93	25

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parenthesis; and standard errors reported under panel A are robust at the zip-code level. This table reports effects of participation in the GreenLeaders program across six locations types (i.e., resort, small/metro town, airport, suburban, urban, and interstate) based on the difference-in-differences (DID) and generalized synthetic control (GSC) models under panel A and B, respectively. Each of the dependent variables (i.e., *Occupancy, ADR,* and *RevPAR*) has been regressed separately by the six location types, and every column represents estimates of the participation effects for a particular location type.

Table 6: Participation effects by city popularity (with matched data)

Dependent Variable	All	Excluding Top 10	Excluding Top 20	Excluding Top 30	Excluding Top 40	Excluding Top 50	Excluding Top 60
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Occupancy	-0.426	-0.335	-0.422	-0.439	-0.872	-0.722	-1.179
	(0.621)	(0.781)	(0.845)	(0.901)	(0.950)	(1.052)	(1.094)
ADR	2.952	3.757	2.428	3.759	5.881	7.793*	9.453**
	(1.886)	(2.958)	(3.072)	(3.269)	(3.542)	(4.220)	(4.560)
RevPAR	2.819*	3.589	2.533	3.501	4.927*	6.819**	7.651**
	(1.465)	(2.339)	(2.503)	(2.660)	(2.924)	(3.287)	(3.475)
N	1,189,228	739,756	664,844	608,660	519,702	397,970	355,832
Number of Hotels	506	316	284	260	222	170	152

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, reported in parenthesis, are robust at the zip-code level. This table reports the effects of participation from the difference-in-differences (DID) model. As we move from column 1 to column 7, I estimate the DID model with the propensity score matched data by incrementally excluding more cities (thereby, the hotels located within) from the top of the city-popularity-rank by TripAdvisor. Column 1 excludes no cities, and Column 7 excludes 60 cities. The table shows if the participating effects vary based on the popularity of the city of a GreenLeaders hotel.

Table 7: STR's Definitions of Location Segments

Location	Definition
Urban	Densely populated location in a large metropolitan area. (e.g., Atlanta, Boston, San Francisco, London, Tokyo).
Suburban	Suburbs of metropolitan markets. Examples are Sag Harbor and White Plains, NY (near New York City, USA) and Croydon and Wimbledon (near London, UK). Distance from center city varies based on population and market orientation.
Airport:	Hotel in close proximity to an airport that primarily serves demand from airport traffic. Distance may vary.
Interstate/Motorway:	Property in close proximity to major highway, motorway or other major roads with the primary source of business via passerby travel. Hotels located in suburban areas have the suburban classification.
Resort:	Property located in a resort area or market where a significant source of business is derived from leisure/destination travel. Examples: Orlando, Lake Tahoe, Daytona Beach, Hilton Head Island, Virginia Beach.
Small Metro/Town:	Area with either a smaller population or remote locations with limited services. Size varies by market orientation. Suburban locations do not exist in proximity to these areas. In North America, metropolitan small town areas are populated with less than 150,000 people.

Notes: This table presents how STR defines each of the location segments.

Figure 1: GreenLeaders hotels on TripAdvisor.com

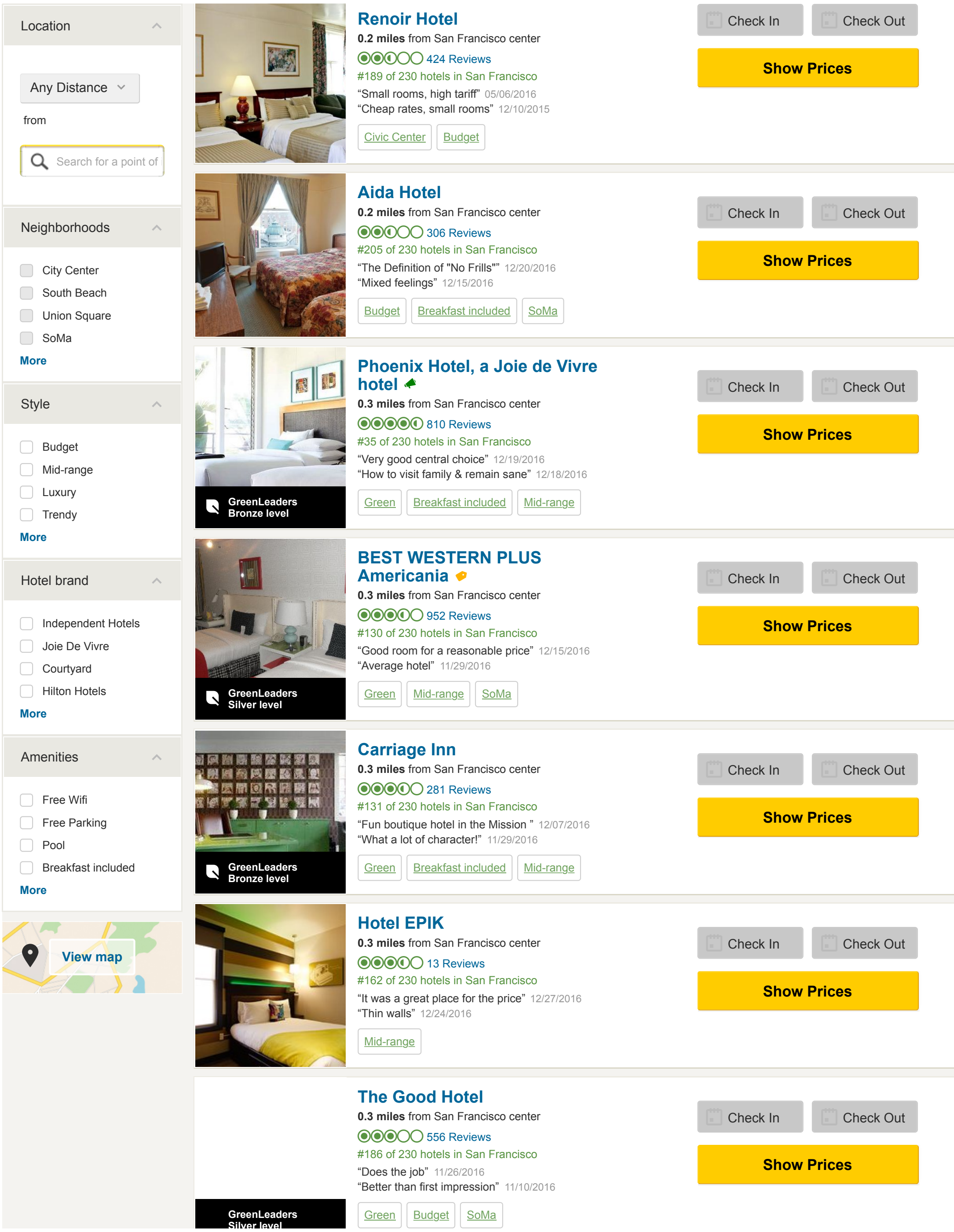


Figure 2: Vertical differentiation in a modified Hotelling model (adapted from Shy 1995)

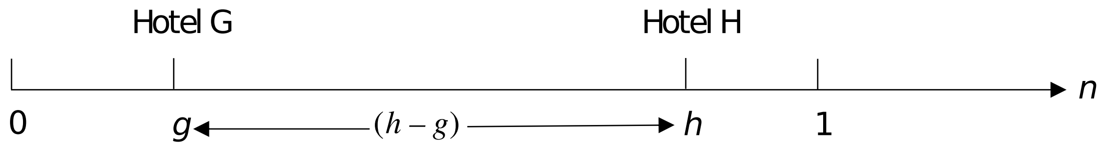


Figure 3: Determination of the indifferent consumer among vertically differentiated hotels. Left: $p_G < p_H$, Right: $p_G > p_H$ (adapted from Shy, 1995)

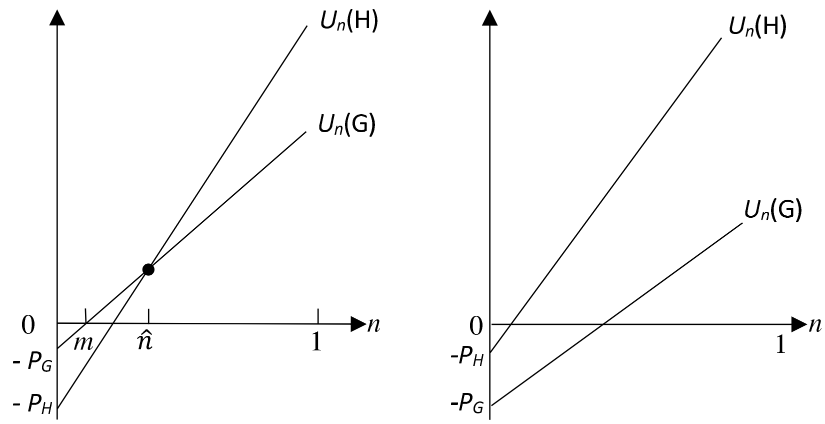


Figure 4: Number of participating hotels by their badge types in the GreenLeaders program between 2013-2016 period.

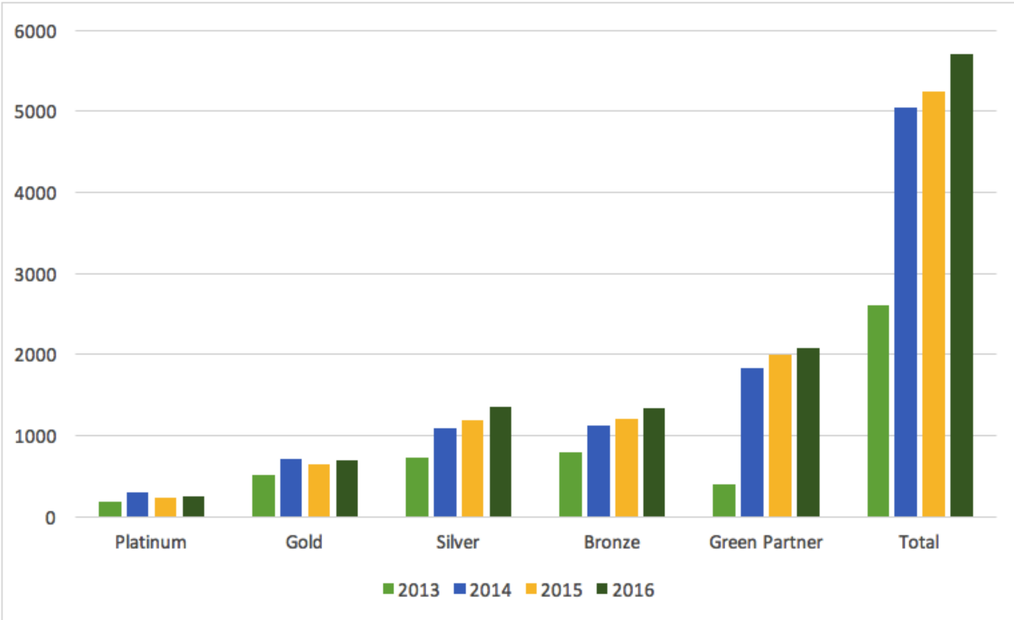
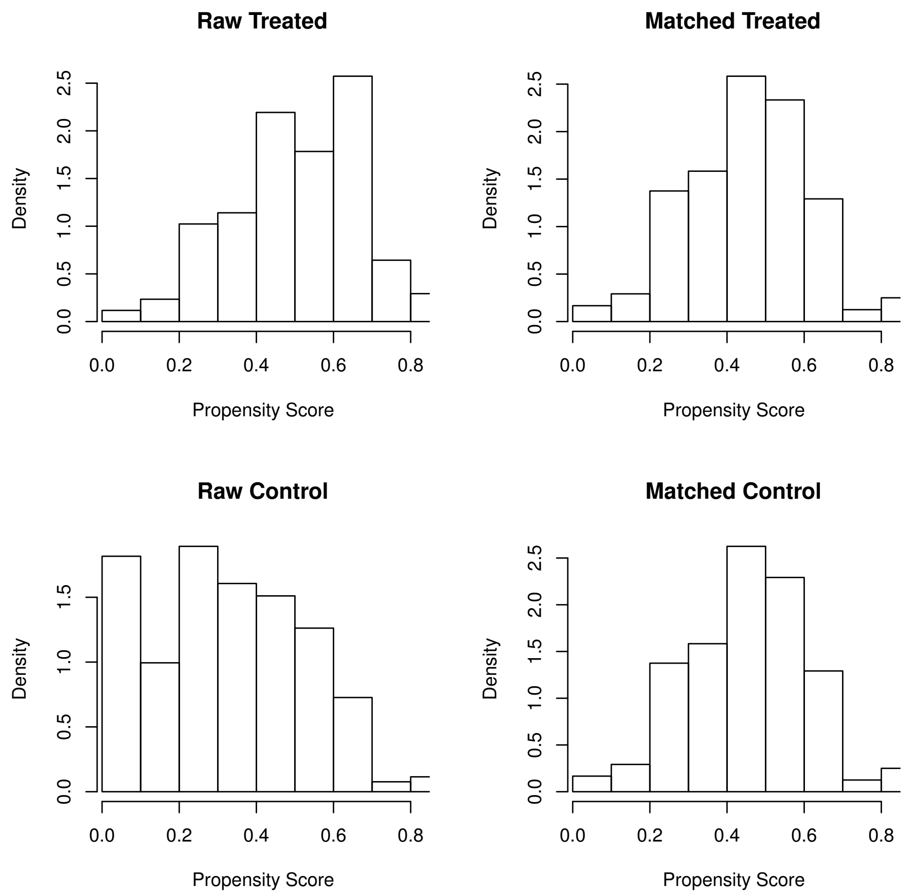


Figure 5: Histogram of propensity scores between treatment and control groups: Raw vs. Matched



Notes: This figure illustrates distributions of the propensity scores for the treated and control units before and after propensity score matching. On the left-hand side, the propensity score distributions are based on the raw data, whereas on the right-hand side, the propensity score distributions are based on the matched data.

Figure 6: Performance of treated and control groups before and after matching