Incumbents' Strategic Responses to Gig Disruptors in the Hotel Industry

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Abstract

Disruptive innovations arising from the gig and sharing economy have placed existential threats on incumbents. We examine the impact of entrants with such innovations on incumbents and how they respond. We argue that the innovations brought by these disruptors differ from past disruptive innovations because they possess architectural advantages over resource-constrained incumbents while growing from a niche to compete with resource-rich incumbents. Accordingly, incumbents need to adjust their positioning by competing on price for resource-constrained incumbents and by competing on quality for resource-rich incumbents. Using property-level hotel data and exploring a regulatory event restricting short-term rentals to address endogeneity concerns, we find that the impact of these disrupters is greater for resource-constrained hotels and responses are heterogeneous across incumbent hotels with different organizational characteristics.

Keywords: Gig and sharing economy, platform, market entry, incumbent response, disruptive innovations

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1 INTRODUCTION

In recent years, disruptive innovations arising from the gig and sharing economy—sharing goods and services via online peer-to-peer exchange platforms on a part-time or temporary basis—have significantly transformed how consumers search for goods and services. This phenomenon, in turn, has created considerable competitive pressures for incumbents, prompting questions about how they should react. In this paper, we explore how incumbents strategically respond based on their resources and positions to these new entrants from the gig and sharing economy (hereinafter gig disruptors) and empirically examine the hotel industry facing short-term rental disruptors such as Airbnb and Vrbo. In particular, our investigation centers on understanding the characteristics and impacts of gig disruptors, taking into account the heterogeneity of resources possessed by incumbents and how this heterogeneity shapes their responses.

Researchers have increasingly directed their attention to the gig and sharing economy. For example, Markman, Lieberman, Leiblein, Wei, and Wang (2021) derive more precise definitions for the sector and provide theory formulation on its value creation and distribution. Empirical studies have also investigated some crucial topics, including industry dynamics (Cramer & Krueger, 2016; Li & Srinivasan, 2019), entrepreneurial decisions (Burtch, Carnahan, & Greenwood, 2018; Koustas, 2019), and societal implications (Edelman, Luca, & Svirsky, 2017; Greenwood & Wattal, 2017). Despite these extant theoretical and empirical investigations, the important strategic issue of how incumbents should respond to competitors from this sector remains underexplored. Examples of such research include the discussion on moral hazards (Liu, Brynjolfsson, & Dowlatabadi, 2021) and price (Zervas, Proserpio, & Byers, 2017) and non-price responses (Chang & Sokol, 2022). Furthermore, notwithstanding the contributions from these studies, the underlying theoretical drivers behind the phenomenon remain less understood.

The hotel industry is one of the industries that were greatly affected by gig disruptors. Despite the long-standing dominance of major hotel chains, by 2018, Airbnb sales in the United States had already exceeded those of Hilton and IHG, trailing only Marriott among the major hotel brands (Gessner, 2019). Researchers have studied various aspects of the competitive dynamics of the industry (Baum & Mezias, 1992; Kalnins & Chung, 2006). However, less is known about the influence of gig disruptors on hotel performance and responses.

While there have been numerous studies around incumbents responding to new entrants (Mitchell, 1989; Simon, 2005; Prince & Simon, 2015), endogeneity issues of incumbent response remain a major concern for management scholars. Such a concern arises because it is empirically challenging to isolate the marginal effects of the entrants alone in many industry contexts. In addition, variations in incumbents' responses are expected due to industry heterogeneity, as incumbents possess different resources and capabilities for addressing threats from entrants. Arguably, it is a tradition in strategic management to predict a firm's strategy and performance depending on its resources and industry structure (Barney, 1991; Peteraf, 1993). Nevertheless, past studies have shown less empirical evidence relative to the theory.

Our study builds upon some important research on incumbents' response to gig disruptors. Chang and Sokol (2022) utilize the number of Airbnb listings in the Taiwanese market and examine the price and non-price responses by hotels within the framework of traditional industrial organization. Similarly, Zervas, Proserpio, and Byers (2017) explore Airbnb's staggered entries into Texas and its impact on hotel prices. Farronato and Fradkin (2022) structurally estimate the parameters of a model of consumer utility and supplier costs after Airbnb's entry in 46 cities in the United States. While these studies offer valuable insights, concerns persist about the entanglement between entrants and economic climates in reducedform estimations and the challenges of incorporating individual hotel characteristics in structural estimations. Specifically, the entry timing of Airbnb is endogenous: Airbnb might enter and expand in cities where the demand for lodging increases or consumer taste changes. For example, consumers traveling to certain cities could be more likely to use Airbnb than those traveling to other cities, especially during times when traveling is more desired and when the adoption of new forms of innovation is more prevalent. Also, in these studies, it is not clear how we can relate incumbents' response to gig disruptors to strategy theories such as disruptive innovations and the heterogeneity of resources and capabilities by incumbents.

In this paper, we develop a theoretical framework and conduct empirical analyses to assess the impact of gig disruptors on incumbents and how incumbents with varying resources respond. To understand the impact, we draw on the disruptive innovations literature. We argue that these disruptors possess unique features due to the architectural innovation (Henderson & Clark, 1990) they hold over many incumbents. Moreover, gig disrupters are distinctively different from past disruptive innovations (Christensen, 1997; Christensen & Raynor, 2003) because they can rapidly capitalize on massive, underutilized assets and coordinate them to swiftly enter and expand in a market. Because of these features, all incumbents need to respond. However, resource-constrained incumbents suffer supply-side disruption in which entrants possess superior capabilities, while resource-rich incumbents face disruption from the demand side in which entrants target niche markets. The impacts and the responses should thus differ. Empirically, we examine incumbent hotels' response to Airbnb using property-level hotel data from 2013 to 2019. To address endogeneity concerns, we exploit a plausibly exogenous regulatory event limiting short-term rentals for difference-in-differences (DID) analyses. We further conduct difference-in-difference-in-differences (DIDID) analyses to explore firm heterogeneity. We find resource-constrained hotels are more affected by the regulation and emphasize their existing competencies by changing prices. However, resource-rich hotels are less affected, and there is some evidence that they adjust quality in response to the disruptors.

Our study makes several important contributions to the strategy literature, especially in the studies of the gig and sharing economy, platform, and market entry. First, we examine the understudied issue of incumbent response to gig disruptors and, more broadly, responses to platform entrants. Research on platform entrants emphasizes the competitive outcomes of network effects (Zhu & Iansiti, 2012), competition with complementors (Gawer & Henderson, 2007), platform governance (Chung, Zhou, & Ethiraj, 2023), and pricing strategies of multisided platforms (Hagiu, 2006). While these studies delve into the competitive landscape within platforms, there is limited research on how non-platform incumbents react to platform entrants. Exceptions include studies on newspapers (Seamans & Zhu, 2014, 2017) and music (Zanella, Cillo, & Verona, 2022). With the growing presence of platform entrants, the issues of incumbent responses deserve further scrutiny.

Second, in our empirical approach, we tackle essential endogeneity concerns that remain unaddressed not only in the gig and sharing economy literature but also in the broader market entry literature. Specifically, we utilize an exogenous regulatory event to isolate the impact of new entrants. This approach enables us to quantify the conditions and magnitudes of incumbents responding to entrants with new types of innovations. Importantly, our approach is applicable to a wide range of industry contexts.

Finally, drawing from mainstream strategy concepts, we develop a theoretical framework to enhance the gig and sharing economy and platform literature, which often lacks a theoretical foundation or seeks to build entirely new theories (Rietveld & Schilling, 2021). Our framework combines disruptive innovation theories with resource perspectives to assess how gig disruptors impact incumbents. We highlight that the impacts on and responses from the incumbents depend on the resources the incumbents possess. Our framework also applies to other types of platform entrants. Relatedly, through our theoretical and empirical inquiries, we bolster the robustness of the platform literature that overly focuses on tech industries by investigating the hotel industry. Overall, we align new phenomena with mainstream strategic management theories in platform studies, answering the calls for greater diversity in empirical settings of platform research while forging stronger links to traditional theoretical frameworks in management (Rietveld & Schilling, 2021).

We organize the rest of this paper as follows. In section 2, we review extant literature relating to this study and develop several hypotheses. Section 3 presents the industry context of this study. Section 4 introduces the data and empirical approach to test our hypotheses and presents our findings. Section 5 discusses the insights and limitations and concludes.

2 THEORY AND HYPOTHESES DEVELOPMENT

2.1 Theory on Disruptive Entrants

As incumbents encounter unprecedented disruptions presented by gig disruptors, we draw knowledge from past literature to understand the nature of these disruptions. In practice, the source of disruption is often multifaceted, and the theoretical considerations can be complex.

2.1.1 Advantages of gig disruptors

The platform of the gig and sharing economy is a type of peer-to-peer (P2P) platform that facilitates trade between large numbers of fragmented buyers and sellers (Einav, Farronato, & Levin, 2016). The emergence of entrants using P2P platforms such as Airbnb, Uber, eBay, Craigslist, LendingClub, and Kickstarter presents a unique challenge for incumbents not only from the innovative components of their business models but also from the linkage of these components. As a result, these new disruptors possess advantages over many incumbents in an architectural way (Henderson & Clark, 1990). Moreover, the innovative activities performed by these disruptors are interconnected, making it challenging for incumbents to respond because it is difficult to change the whole value chain due to various sources of inertia (Rumelt, 1995). Similarly, management scholars have approached this issue from various lenses, such as activity systems and barriers to imitation (Porter, 1996; Porter & Siggelkow, 2008; Siggelkow, 2011) and inertial and adaptive views of strategic renewal (Albert, Kreutzer, & Lechner, 2015). It is generally agreed that the interdependencies of activities significantly affect an organization's ability to invoke change in its activity choices and outputs.

Gig disruptors such as Airbnb and Uber are even more disruptive than typical P2P platform entrants because opportunity costs for suppliers of goods or services are low due to the temporary nature of trade. The suppliers provide their underutilized excess time or resources (Gerwe & Silva, 2020), so as long as their marginal cost is covered, they can appreciate the benefits of trade. By using the platform to coordinate these underutilized assets, gig disruptors can enter and expand in a market very quickly in a massive manner without incurring investments in capital assets such as rooms or cars. Therefore, gig disruptors are distinctively different from past disruptive innovations (Christensen, 1997; Christensen & Raynor, 2003), necessitating all incumbents to respond in some way. Moreover, by providing tools for suppliers to share goods and services using underutilized resources, these entrants increase the efficiency of the economy, reduce costs for consumers, and lead to a more optimal allocation of resources (Filippas, Horton, & Zeckhauser, 2020). Gig disruptors thus generate unprecedented disruptions.

To illustrate the disruptions incumbents face from gig disruptors, Figure 1 presents a version of Airbnb's value chain. The vertical green boxes, for example, represent Airbnb's primary activities, and the horizontal blue boxes denote the support activities. As illustrated, the gig and sharing nature of Airbnb allows it to excel in numerous components of its activities. For example, Airbnb has lower logistics and operations costs than hotels because the responsibilities of providing and listing accommodations and managing guests fall to the hosts, to whom Airbnb does not provide physical assets and other inputs. Airbnb also enhances the customer experience by providing targeted local experience and customer support while emphasizing an ecosystem of high-rated hosts and guests facilitated by its innovations. Moreover, these activities are interconnected and mutually reinforce one another in a gig environment, giving rise to systematic advantages as an architecture. Even though incumbent hotels could attempt to match one or a few of these activities, they would not be able to replicate the whole interlocking system.

--- Insert Figure 1 about here ---

2.1.2 Entrants with disruptive innovations

While generations of management scholars have studied the process of technological innovation entering a market and eventually replacing the incumbents, the notion of disruptive innovations is most popularized by Christensen's proposition that they "attack from below" with inferior but good-enough products (Christensen, 1997; Christensen & Raynor, 2003). Christensen's model entails that the disruptors originate in low-end markets and then enter the mainstream by providing acceptable products or services to these customers through continuous improvements, allowing the disruptors to successfully capture market shares.

Another stream of research that posits new entrants with inferior initial performance is best represented by Foster's S-curve model (Foster, 1986). The Foster model predicts that these inferior technologies would eventually mature and achieve superiority as the incumbents wait too long until the entrants reach the crossing point of the S-curve, when it becomes too difficult to compete with them. In contrast, the Christensen model predicts that disruptive innovations will never achieve superior performance and yet take over the incumbents' market shares.

Furthermore, other research has also studied scenarios in which new technologies can outperform incumbents from the start (Cooper, Demuzzio, Hatten, Hicks, & Tock, 1973; Tushman & Anderson, 1986; Anderson & Tushman, 1990). Notably, the Tushman and Anderson model introduces the concepts of competence-destroying or competence-enhancing innovations, examining how new technologies reduce or eliminate critical competencies of the incumbents. Subsequent research has investigated the process of creative destruction and the survival conditions of incumbents (Utterback, 1994; Tripsas, 1997; Rothaermel & Hess, 2007). Overall, this stream of research emphasizes the performance superiority of the new entrants throughout the substitution process, resembling an "attack from above" on the incumbents.

This literature suggests that the threats from disruptive innovations can come from below or the top through different processes, implying that incumbents need to ascertain the nature of disruption to survive and prosper in the evolving technological landscape.

2.1.3 Incumbents responding to gig disruptors

Understanding how incumbents should respond entails characterizing the challenges presented by the types of innovations discussed above. Gans (2016) further identifies two sources of disruption: the demand side and the supply side. In Gans's language, demand-side disruption happens when successful firms focus on their main customers and underestimate market entrants with innovations that target niche demands. In contrast, supply-side disruption occurs when firms focused on developing existing competencies become incapable of developing new ones.

Connecting Gans's arguments to Christensen's model, we can see that demand-side disruption is more prominent when incumbents face an attack from below. In this case, incumbents tend to underestimate the threats growing from a niche end of the market. Even when they realize such threats, they face a resource reallocation dilemma dealing with inferior entrants. After all, it is difficult to justify directing resources to markets where sales will be relatively small when fulfilling the requirements of reliable customers entails attractive profit margins (Bower & Christensen, 1995). However, the inferior technologies can gradually win over an increasing extent of consumers' willingness to pay because even those once reliable, profitable customers will eventually switch to the disruptors' products and services. Hence, incumbents' responses (or lack thereof) to attack from below are dictated by demand conditions such as customers' willingness to pay (Adner, 2002; Adner & Zemsky, 2006).

Foster's S-curve disruption presents related conditions for incumbents to respond effectively. While entrants still begin by attacking from below, they come with the promise of eventual superiority. Adner and Lieberman (2021), for example, argue that incumbents need to consider whether to invest early in an emerging technology before its superiority is established. While there is the risk of giving away market shares, incumbents also need to assess their opportunity costs of allocating resources away from their existing technologies because the new entrants do not face the same opportunity costs. This asymmetry arises because entrants have no existing market to lose (Reinganum, 1983). In both cases, when incumbents face an attack from below, they need to decide how to reallocate their resources.

Incumbents facing attack from above, however, encounter more competitive pressure from supply-side disruption. This is because new entrants typically bring innovations that offer performance improvement. However, supply-side organizational factors outlined by Henderson and Clark (1990), such as the innovative architecture of the new products and services and the incumbents' existing value chain, restrict incumbents' potential responses. In this case, the presence of new technologies is often competence-destroying (Tushman & Anderson, 1986; Anderson & Tushman, 1990), and the incumbents are hindered in their capabilities to develop new competencies during these technological shifts.

Incumbents' vulnerability to demand-side or supply-side disruption from gig disruptors hinges on their market position. Despite their architectural innovation, gig disruptors do not necessarily possess superior value propositions over all incumbents. Because of the temporary and uncertain nature of the suppliers of goods and services the entrants gather, they cannot provide the same credibility to their offerings as established incumbents (Garud, Kumaraswamy, Roberts, & Xu, 2022). While the entrants can offset this credibility gap with rating and feedback systems to their offerings (Xu, Lu, Ghose, Dai, & Zhou, 2023), consumers might still view their offerings as inferior to the incumbents with established market positions, brands, and track records (Zhang, Nan, Li, & Tan, 2022). Therefore, the entrants act as demand-side disruption for incumbents with superior market positions and grow from a niche, while they function as supply-side disruption for incumbents with lower quality and less established market positions.

Whereas gig disruptors possess valuable components and architectural knowledge over many incumbents, incumbents with abundant capabilities can reallocate their resources to adjust and consolidate their positioning. Incumbents' potential responses to these disruptors thus differ. Resource-constrained incumbents need to search for ways to survive and renew, facing interconnected activities with architectural advantages from supply-side disruption. In contrast, resource-rich incumbents face the trade-off between focusing on the established markets and investing in emerging innovations by dealing with the evolving thresholds of customers' willingness to pay for acceptable products, the tension caused by demand-side disruption.

2.2 Hypothesis Development

2.2.1 Impacts on incumbents

Based on the discussions above, we can make some assertions on the impacts on incumbents facing uneven disruption. Regardless of the type of disruption, what seems inevitable is a process of substitution for the incumbents (Christensen, 1997; Foster, 1986; Tushman & Anderson, 1986; Gans, 2016), which entails some degree of market shares being captured by disruptors. Hence, incumbents facing disruption should experience downward pressure on performance (Allen, 1950). In our empirical setting, we isolate the marginal effects of disruption from other forces by examining the introduction of a regulation that illegalizes gig disruptors. The regulatory shift should ease the pressure from gig disruptors and positively affect incumbents. Because of this setting, when we formulate our hypotheses, we contrast the increase and ease of competition from gig disruptors. Our first hypothesis, serving as the baseline hypothesis, is thus:

Hypothesis 1. *The increase (ease) of competition from gig disruptors negatively (positively) impacts the performance of incumbents.*

While we anticipate an overall substitution effect, the impacts of the increase or ease of competition from gig disruptors are unlikely to be homogeneous, given the industry structure. As discussed earlier, we posit that gig disruptors introduce architectural innovations over resource-constrained incumbents, which have limited capabilities of developing new competencies (Henderson & Clark, 1990). This process is best represented as a supply-side disruption that predominantly affects these incumbents because of their lack of resources and capabilities for strategic renewal (Rothaermel & Hess, 2007; Teece, 2007; Helfat et al., 2007; Capron & Mitchell, 2009). Consequently, forces that change the impact of these disruptors' operations are more likely to influence incumbents with limited resources and weaker market positions. In contrast, incumbents facing demand-side disruption tend to possess more resources and capabilities to avoid becoming severely impacted by new entrants from the beginning. Thus:

Hypothesis 2. *The increase (ease) of competition from gig disruptors more negatively (positively) impacts the performance of resource-constrained incumbents.*

2.2.2 How incumbents need to compete

The next logical question is on which dimensions incumbents need to compete when they face gig disruptors. While there are myriads of strategic dimensions for incumbents to consider, their response should align with the nature of the disruption they confront (Gans, 2016) and the resources and capabilities they possess (Teece, 2007; Helfat et al., 2007). Incumbents facing supply-side disruption are typically positioned at the lower end of the industry spectrum and have limited capabilities (Utterback, 1994; Lavie, 2006) to develop new competencies. Furthermore, even when they can develop new knowledge and skills, they often lack incentives to do so and rationally opt for displacement over time (Arend, 1999; Hill & Rothaermel, 2003). In either case, the opportunity costs associated with acquiring new competencies are prohibitively high, and resource-constrained incumbents might find greater benefits from alternative strategies that ensure their survival in the present. As a result, we hypothesize that these lower-end incumbents will increasingly rely on their existing competencies and resort to price competition rather than focusing on enhancing the quality required to participate in the new technological shifts. Thus:

Hypothesis 3. *As the competition from gig disruptors intensifies (eases), resource-constrained incumbents are more likely to lower (raise) their prices.*

In contrast, incumbents positioned at the high end of the industry spectrum possess more resources and capabilities to respond to demand-side-driven disruption from gig disruptors. The issues are whether or when they fully realize the necessity of responding (Christensen, 1997; Christensen & Raynor, 2003) and, even so, how many resources they should reallocate, facing asymmetric opportunity costs (Bower & Christensen, 1995; Adner & Lieberman, 2021). On the one hand, the resources they reallocate in response to gig disruptors are rarely profit-maximizing. On the other hand, doing so might reduce the risk of eventually being displaced. While firms often focus on achieving high current efficiency (Levinthal & March, 1993), the resource-rich ones tend to invest in new ventures to harness new knowledge (Dushnitsky & Lenox, 2005).

Furthermore, the core customers of the resource-rich incumbents are more price-insensitive and more willing to pay for products and services with greater quality. In such a case, the optimal response to intensified competition by gig disruptors would involve improving quality to retain their customer base. It is found that firms respond to competition by increasing service quality in various industries, such as supermarkets (Matsa, 2011), music (Zanella et al., 2022), and nursing homes (Gandhi, Song, & Upadrashta, 2023). A common theme in these studies is that quality enhancements are mainly driven by more capable and resource-rich firms' attempts to differentiate when they face disruptions.

An essential consideration for the focal, resource-rich incumbents is whether they should respond to gig disruptors at all, given that gig disruptors might not be their direct substitutes. But even so, incumbents one level lower in the industry spectrum need to compete more directly with gig disruptors. Then, the offerings from these incumbents can become closer substitutes to the focal incumbents and might attract the focal incumbents' core customers, necessitating a response by the focal incumbents. Therefore, we posit that the resource-rich incumbents should establish a substantial degree of willingness to make quality changes to stay competitive. Thus:

Hypothesis 4. *As the competition from gig disruptors intensifies (eases), resource-rich* *incumbents are more likely to raise (reduce) their quality.*

3 INDUSTRY CONTEXT: THE HOTEL INDUSTRY

3.1 The Hotel Industry Facing Gig Disruptors

We examine the hotel industry for our empirical analysis. Hotels have always been an essential part of consumers' lives. In 2022, there were over nine million hotel and motel rooms in the United States alone, representing a $189 billion industry (American Hotel and Lodging Association, 2023). At the same time, a wide range of hotel options is offered to consumers, be it a luxurious suite at the top of a skyscraper or a simple room that fits parsimonious budgets. Despite various lodging options like lodges, glampers, cruise ships, and motor homes, hotels remain the most popular vacation accommodation by far, with over half of all U.S. adults choosing hotels over any other option in 2022 (Appelbaum, 2023).

However, the emergence of short-term rental competitors and their magnitude necessitates hotels to revisit their existing strategies. While hotels remain a popular accommodation option, gig disruptors such as Airbnb and Vrbo have become a force to be reckoned with. Compared with hotels, these disrupters allow hosts to list their properties for short-term rental purposes and have gained increasing popularity among homeowners and travelers. For example, a typical Airbnb host in the United States earned $14,000 in 2022, and as of December 2022, there were more than four million Airbnb hosts worldwide and more than 100,000 cities and towns with active Airbnb listings (Airbnb, 2023).

3.2 Heterogeneity of the Hotel Industry

It is vital to notice that the hotel industry is far from homogeneous, and the comparisons vis-à-vis short-term rental disruptors are also multidimensional. A potential traveler may evaluate a wide range of criteria, such as staff availability, food, transportation, and amenities, to select her choice of accommodation. Therefore, while gig disruptors may disrupt the hotel industry as a whole, the heterogeneity in hotels can present more nuances that make them excel in certain dimensions over the disruptors but lack in others.

An important observation is that an average hotel room is 29% cheaper than booking an Airbnb for two travelers, but an average Airbnb for six travelers is 33% cheaper than hotel rooms (French, 2023). Although this can seem paradoxical, further consideration of the levels of hotel heterogeneity can shed light on this phenomenon (Arbelo, Arbelo-Pérez, & Pérez-Gómez, 2021).

3.3 Anecdotal Perspectives from Hoteliers

The rich heterogeneity in hotels implies that incumbent hotels may perceive the threat of short-term rental disruptors differently. Anecdotes offer some potential insights into hotels' strategic responses. For example, in 2017, Geraldine Calpinc, the Chief Marketing Officer of Hilton Worldwide, defended Hilton's value proposition and dismissed Airbnb as a lodging company:

> *"We are in the business of people serving people. We are in hospitality, which is in some ways a little different than some of the more new entrants that are into more lodging. We offer consistency in the brand, we offer security. . . . You know when you are going to stay in a Hampton by Hilton or a Hilton, you know what you are going to get. And we consistently ensure that we deliver that and that business of people serving people, that hospitality, the beautiful smile that you get from team members when you walk into one of our hotels is, I believe, different than some of the other new lodging companies.*" (Handley, 2017)

Here, the threats of the new "lodging companies" do not seem to be well recognized. It remains unknown if Calpinc intentionally downplayed such threats. Nonetheless, it is clear that she wanted to showcase her confidence in Hilton's organizational capabilities to compete in the "hospitality" business of people serving people.

On the contrary, in 2018, Justin Salisbury, the owner of four boutique hotels, worried about facing the disruption from Airbnb:

> *"Airbnb has done a lot in terms of exposing millennials to travel and is forcing everyone to up their game. People are looking for experiences. Hotels now have more pressure to provide more than a room.*" (Bearne, 2018)

Here, the substantial disruption for less established incumbents is well acknowledged. Further, it is suggested that such disruption comes mainly from the supply side. While the less resourceful incumbents recognize the competitive pressure, it is unclear if they possess the necessary capabilities to respond.

Together, this anecdotal evidence from hoteliers shows different perceptions regarding the threats of Airbnb, which result from the difference in market position and capabilities of the hotels. It also suggests that the response should differ accordingly. These differences provide an ideal setting to examine incumbents' strategic responses to these disruptors.

4 DATA AND EMPIRICAL APPROACH

4.1 Hotel Data

To examine the hypotheses, we obtained hotel property-level data from STR, LLC, a market research company specializing in the hotel industry. Our data include monthly performance metrics on hotel revenue, price, and occupancy, along with annual profit and liability data from numerous revenue and expense sources. These hotel properties are anonymized by STR. We use data from January 2013 to December 2019 for our main empirical specifications for several reasons. First, when Airbnb was founded in August 2008, its initial impact on the hotel industry was minimal. However, following multiple rounds of funding and expansion, in 2013 it was first shown to generate significant economic activities in New York City (NYC), a major geographic area of our data coverage (HR&A Advisors, 2013). In addition, by winter 2012, various measurements of the U.S. economy gradually recovered from the unusually prolonged period of deficient demand following the 2008 financial crisis (Lavender & Parent, 2012). Finally, to avoid the confounding effects of COVID-19, we use data prior to the beginning of 2020, when COVID-19 was declared a pandemic by the World Health Organization and a national emergency in the United States with multiple travel bans implemented by the Trump administration. Our data also include several hotel property characteristics, such as operation types, class, location, size, and open year, measured in numerical scales except for the open year, explained in Table 1. We also have identification codes for the chains and parent companies of these hotel properties. We analyze hotels in NYC and the adjacent areas in New Jersey, including the Bergen-Passaic, Newark, and Central New Jersey markets, to utilize the regulatory change explained below. Table 1 reports summary statistics of selected hotel metrics in a frequency of hotel-month observations for hotels within NYC and New Jersey.

--- Insert Table 1 about here ---

4.2 Legislation on Short-Term Rentals

To isolate other factors that may affect hotel performance, such as economic cycles and changes in consumer taste, we leverage a regulatory change that restricts the operation of short-term rentals. Specifically, we compare the regions that have introduced a regulation to limit short-term rentals and the nearby regions that do not have such a regulation. We then examine the changes before and after the introduction of the regulation. Thus, we employ a DID model to estimate the effects of such a regulation on outcomes measuring hotel performance and responses.

New York State had an early history of regulating short-term rentals prior to the popularization of Airbnb. In 2010, the state passed the first short-term rental regulation, making it illegal to rent out an apartment unit for fewer than 30 days in most apartment buildings. Although this legislation would apply to short-term rental disruptors such as Airbnb, many hosts in New York still rented out their homes as Airbnb started to boom in the city, resulting in an affordable housing crisis (Stringer, 2018). Hence, in October 2016 New York governor Andrew Cuomo signed a state law making it illegal to advertise entire unoccupied apartment units for fewer than 30 days on short-term rental platforms and vowed to enforce the new regulation (or the Airbnb law). The law imposed a maximum fine of $7,500 per violation. A widely reported federal lawsuit was immediately brought by Airbnb and was dropped on the condition that New York City agreed to enforce the law by fining hosts instead of the platform. New York City also required Airbnb to disclose details about its hosts and listings in 2018, but this disclosure requirement does not directly further prohibit Airbnb listings. While discussions about regulating short-term rental disruptors have occurred nationwide, a similar regulation did not become effective in New Jersey until 2020. This timing enables us to construct a longitudinal dataset using treatment and control groups to obtain an appropriate counterfactual to estimate the effects on hotel performance and responses.

One key assumption underlying the causality of our estimates is that the policy change in short-term rental regulation is exogenous to hotel performance in the region. While we cannot entirely rule out the possibility of hotel groups exerting influence on legislators, we collected qualitative and quantitative evidence to demonstrate the plausible exogeneity of the 2016 Airbnb law. First, it was widely reported that other, more pressing externalities, such as the exacerbating housing crisis, prompted Governor Cuomo to sign the state bill into effect. Richard Azzopardi, the spokesperson for the New York State government, for example, defended the legislation:

"This is an issue that was given careful, deliberate consideration, but ultimately these activities

are already expressly prohibited by law. . . . They [Airbnb] also compromise efforts to maintain and promote affordable housing by allowing those units to be used as unregulated hotels, and deny communities significant revenue from uncollected taxes, the cost of which is ultimately borne by local taxpayers."

Also, we use data from Google Trends, an index measuring the relative Google search volume, to show the lack of anticipatory effects prior to the Airbnb law. Figure 2 plots the relative volume of the "Airbnb law" search term in NYC since Google redefined its geographic assignment in 2011. The figure shows an absence of significant pre-trends before the bill was passed in July 2016 and signed into law in October 2016. Hence, it is plausible that most hotels and potential Airbnb hosts were unaware of the new regulation until its passage and enactment.

--- Insert Figure 2 about here ---

4.3 Empirical Specification

To take advantage of the legislation to test our hypotheses, our DID regression models take variations of the following form:

$$Log(y_{ijs(k)t}) = \beta \times NY_{s(k)} \times After\ Airbnb\ Law_t + \gamma' X_{ijs(k)t} + \delta' C_{s(k)t} + \alpha_j + \eta_k + \theta_t + \varepsilon_{ijs(k)t} \quad (1)$$

Where the dependent variable $Log(y_{ijs(k)t})$ denotes our logarithmized outcome measures to be detailed in the next subsection for hotel *i* belonging to hotel chain *j* in state *s* of market *k* at time *t*; $NY_{s(k)} \times After\ Airbnb\ Law_t$ equals to one for state *s* of market *k* subject to the Airbnb law at time *t*; $X_{ijs(k)t}$ is a set of hotel characteristics, including class, size, location, open year, and operation types. $C_{s(k)t}$ is a set of macroeconomic controls, such as the unemployment rate and the number of hotels in the same market. The model also includes hotel chain, market, and time fixed effects, which absorb the individual coefficient terms for $NY_{s(k)}$ and $After\ Airbnb\ Law_t$, to control for their unobserved heterogeneity and shocks. Our primary coefficient of interest is β, whose magnitude implies outcome *y* will change by $100 \times \beta$ percent when $NY_{s(k)} \times After\ Airbnb\ Law_t$ equals one. Furthermore, we also estimate variations of the following DIDID model to empirically test the heterogeneous impacts and responses among hotels.

$$Log(y_{ijs(k)t}) = \beta_1 \times NY_{s(k)} \times After\ Airbnb\ Law_t + \beta_2 \times NY_{s(k)} \times x_{ijs(k)t} + \beta_3 \times After\ Airbnb\ Law_t \times x_{ijs(k)t} + \beta_4 \times NY_{s(k)} \times After\ Airbnb\ Law_t \times x_{ijs(k)t} + \gamma' X_{ijs(k)t} + \delta' C_{s(k)t} + \alpha_j + \eta_k + \theta_t + \varepsilon_{ijs(k)t} \quad (2)$$

where $x_{ijs(k)t} \in X_{ijs(k)t}$ is a selected hotel characteristic, such as a hotel being classified as economy. In this case, a one-unit change in $NY_{s(k)} \times After\ Airbnb\ Law_t$ implies a $100 \times \beta_4$ percent change in outcome *y* for economy hotels relative to the omitted category, such as luxury. The total marginal effect of an economy hotel in a regulated region is thus $\beta_1 + \beta_4$, which is associated with a $100 \times (\beta_1 + \beta_4)$ percent change in outcome *y*. We use hotel characteristics such as class (six scales from economy to luxury), size (five scales using the number of rooms), and location (urban, suburban, airport, and small town) as measures of their resources. Economy hotels inherently possess fewer resources than luxury hotels due to limitations in the quality and quantity of labor, amenities, and their reputation. This argument can also extend to smaller hotels competing against larger establishments. While some may argue that hotels near airports cater to business travelers, they mostly offer fewer amenities and have smaller staff sizes than their urban counterparts. Furthermore, the NYC areas represent a unique case where the bustling nature of the urban cores results in hotels in those locations assuming much stronger market positions.

In addition to the plausibly exogenous nature of the regulation discussed earlier, we consider the parallel trends assumption, which requires the difference between the treatment and control groups to be constant over time in the absence of treatment. While there are recent debates on why researchers cannot fully test this assumption (Freyaldenhoven, Hansen, & Shapiro, 2019; Rambachan & Roth, 2023), we adopt recent practices used in leading economics journals to conduct an event study to formally test for the pre-trends (Deschenes, Greenstone, & Shapiro, 2017; Markevich & Zhuravskaya, 2018). This approach allows us to check for parallel trends between treatment and control groups prior to treatment. To account for the seasonally sensitive nature of hotel performance, we group periods into six months, with the period immediately prior to the start of treatment as the omitted period. Figure 3 plots the coefficient estimates of the time-to-regulation effects on hotel revenue and shows no apparent violation of the parallel trend assumption.[1] Thus, our empirical strategy allows us a causal estimation to mitigate some endogeneity issues from past studies on incumbent responses facing disruptors.

--- Insert Figure 3 about here ---

4.4 Empirical Results

Table 2 reports the effects of short-term rental regulation on the performance of incumbent hotels, using the natural logarithm of a hotel's deflated revenue per available room per day as the outcome. The logarithmization of the dependent variable allows us to estimate the impacts in elasticity terms. For example, Model 1 employs a DID model and shows that hotels in regions subject to the short-term rental regulation, on average, experience a 3.5% increase in revenue compared to hotels in regions without these regulations (p = .007). As predicted by our

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[1] Specifically, Figure 3 implements the following leads and lags specification: $Log(Y_{ijs(k)t}) = \beta_0 + \beta_1 \cdot treat_{s(k)t} + \sum_p \varphi_p \cdot 1[t = p] + \sum_p \lambda_p \cdot treat_{s(k)t} \cdot 1[t = p] + \gamma' X_{ijs(k)t} + \delta' C_{s(k)t} + \alpha_j + \eta_k + \theta_t + \varepsilon_{ijs(k)t}$, where the sums are over all but the period immediately prior to the start of treatment. Each dot with a capped spike is the coefficient estimate of λ_p for the corresponding leads and lags in reference to the last pre-treatment period. Coefficients are not statistically different from 0 until on or after the treatment, which supports the parallel trends assumption needed for DID analysis.

Hypothesis 1, this result shows that such a regulation positively impacts the performance of incumbents, presumably by hampering the substitution process from the disruption.

Models 2 to 4 in Table 2 further investigate the heterogeneity in hotel performance by looking into different categories of hotels using DIDID models. Model 2 provides suggestive evidence that economy hotels benefit from a 15.5% relative increase in revenue compared to luxury hotels ($p = .075$). Model 3 shows that smaller hotels, such as those with fewer than 75 rooms, see a 22.7% relative increase in revenue compared to large hotels with more than 500 rooms ($p = .000$). Model 4 finds that hotels in remote locations, such as those near airports, profit 10.6% more than hotels in urban NYC areas ($p = .025$). These models support our Hypothesis 2 that resource-constrained incumbents are more likely to benefit from the regulation.

--- Insert Table 2 about here ---

To test our Hypothesis 3, that resource-constrained incumbents are more likely to raise their prices after the ease of competition from gig disruptors, Table 3 presents regression results using hotels' deflated daily rates as an outcome. Model 1 shows that, on average, hotel prices in regulated regions do not change much compared to those in non-regulated regions after implementing the short-term rental law. However, Model 3 shows that small hotels, such as those with fewer than 75 rooms, raise their prices by 15.1% relative to large hotels, such as those with more than 500 rooms ($p = .002$). Model 4 further shows that hotels in more remote locations, such as those near airports, raise prices by 10.8% compared to those in urban areas following the ease of competitive pressures from short-term rentals ($p = .000$). Taken together, these results broadly support our Hypothesis 3 and demonstrate that lower-end incumbents tend to rely on their existing competencies and compete on price when facing gig disruptors.

--- Insert Table 3 about here ---

Although empirical results discussed above utilize monthly hotel data in our regions of interest, we need to switch to annual data to get at our Hypothesis 4, that resource-rich incumbents are more likely to reduce their quality when the competition from gig disruptors eases. Note that infrequent observations reduce statistical power. Table 4 reports results using hotels' decisions to keep track of their food and beverage costs or not as an outcome. In line with the tradition in the hospitality literature, the awareness of food and beverage expenses is a well-established indicator of a hotel's service quality (AbuKhalifeh & Som, 2012; Cronin & Taylor, 1992). While this measure is not perfect, it reflects some degree of resource reallocation of incumbent hotels toward enhancing their overall quality. We estimate a linear probability model.

While results from Table 4 provide some insights regarding the heterogeneity in hotel responses with respect to quality investment, the picture is arguably murkier here. Model 1 indicates that the average hotel service awareness does not statistically differ between regulated and non-regulated regions ($p = .563$). But Model 3, for example, provides suggestive evidence that large hotels (500+ rooms) pay 15% less attention to service quality relative to smaller hotels (75–149 rooms) after the short-term rental regulation ($p = .074$). However, it also shows that the total marginal effect of lessened disruption on large hotels' quality response is smaller and positive (e.g., $100\% \times (-0.15 + 0.188) = 3.8\%$). Model 4 also shows some suggestive evidence that urban hotels overlook service quality by 13.7% relative to hotels near airports ($p = .126$), with a small total marginal effect ($100\% \times (-0.137 + 0.132) = \ 0.5\%$). We also use different quality measures such as total expenses for room, labor costs for room, total expenses for food and beverage, and labor costs for food and beverage, but the results are inconclusive due to infrequent observations and lack of statistical power. There are some possible explanations. One possibility is that resource-rich incumbents are reluctant to reduce quality under competition for fear of a compromised reputation (Höner, 2002). Another possibility is that, while price adjustments can be implemented quickly, deciding to change and implement quality-enhancing investments requires more time (Prince & Simon, 2009), and these decisions may not be made in the three-year period after the introduction of the Airbnb law. Furthermore, some high-end incumbents might disregard the change of the threats from the short-term rental disruptors as they attend to a niche end of the market. As a result, although these incumbents are abundant in their resources, they underestimate the urgency of responding to disruptors.

--- Insert Table 4 about here ---

4.5 Robustness Checks

We perform several alternative specifications to demonstrate the robustness of our results. First, we implement coarsened exact matching (CEM) to create a matched sample to improve the estimation of causal effects by reducing the imbalance in covariates between treated and control groups. We then reestimate our DID and DIDID specifications. CEM offers many advantages over traditional matching methods, such as propensity score matching, in reducing covariate imbalance and effect bias because of its more accurate and less restrictive balance-checking procedures (Iacus, King, & Porro, 2012). Thus, CEM is increasingly used in related strategy research, such as platform governance and its entry threat on complementors (Zhang, Li, & Tong, 2022; Wen & Zhu, 2019). We match the three main hotel characteristics (class, size, location) and successfully reduce the multivariate and univariate imbalances to near zero. Thus, it minimizes the differences between NYC and NJ hotel characteristics in the pre-treatment periods, making our estimations more credible in meeting the parallel trend assumption. The results, as shown in Tables A1 to A3 in the Online Appendix, are similar to our baseline results.

One might suspect that the factors that influence the short-term rental regulation and

Airbnb activities might vary within a state or even a finer market over time, confounding the estimates of the market fixed effects. To address this possibility, we incorporate alternative econometric functional forms proposed in leading economics journals (Friedberg, 1998; Wolfer, 2006) to allow unobserved propensities of Airbnb activities to trend linearly and even quadratically over time in different markets. The results with linear market-specific trends, as shown in Tables A4 to A6 in the Online Appendix, are similar to our baseline results. Results for further incorporating quadratic market-specific trends are almost identical to linear trends results.

One might also argue that the Airbnb regulation did not yield any material results in the activity of Airbnb for reasons such as the lack of enforcement. To test such a possibility, we obtained Airbnb listings data from Inside Airbnb, which scrapes monthly Airbnb listings data, and conduct DID analyses. The data are only available from June 2015 and include 11 non-consecutive months of observation before and 36 months after October 2016, when the short-term rental law came into effect in New York. As Table A7 in the Online Appendix shows, Airbnb's growth has been clearly deterred in New York City after the introduction of the regulation. We further incorporate Airbnb growth as a covariate in our specifications to account for listings from non-compliant hosts and obtain similar results, as shown in Tables A8 and A9.

5 DISCUSSION AND CONCLUSION

5.1 Summary of Findings

This paper explores incumbents' strategic responses to emerging gig disruptors. We characterize drivers behind supply- and demand-side disruptions and their implications for incumbents. We then discuss the heterogeneity of incumbents that face these disruptions from gig disruptors. Next, we systematically consider incumbent responses based on their resources and capabilities. To address endogeneity issues in past research concerning incumbent responses, we leverage a plausibly exogenous shock. Using hotel data and variations in the regulatory change concerning short-term rental disruptors, our DID and DIDID estimates suggest that the ease in competitive pressures positively impacts the performance of incumbents, especially those more constrained in their resources and capabilities. Further, we find non-homogeneous responses from incumbents with different characteristics. While we find support that resource-constrained incumbents are more inclined to engage in price competition, resource-rich incumbents do not necessarily adopt a differentiation strategy. However, they do seem to invest more in quality relative to the resource-constrained incumbents. Overall, our findings discern the performance impacts of gig disruptors and the conditions for incumbents to respond effectively.

5.2 Performance Implications

Our theoretical arguments outline the performance impact for incumbents with varying resources facing different sources of disruption from gig disruptors. Important managerial implications follow that incumbents who respond correctly in our framework should outperform those who respond incorrectly. To validate this, we compare the differentials in performance outcomes for the resource-constrained hotels that should raise their prices as the competition from Airbnb eases due to the legislative change in October 2016. To do so, we compute the changes in hotel prices between September 2016, one month before the Airbnb law took effect, and September 2019. We split our sample for those hotels with price changes above the average and those below the average. Using these subsamples, we analyze both interaction effects and further subsampling resource-constrained incumbents to show that hotels that respond correctly would achieve better results. Due to fewer observations with the subsample analyses, we merge certain categories of hotels, so the estimations are based on coarsened, more conservative subsamples. As shown in Tables A10 to A15 in the Online Appendix, resource-constrained incumbents, such as hotels that are midscale or economy, have fewer than 75 rooms, or are located near the suburban, airport, or small metro areas, perform better than similar hotels when they implement above-average changes in price. For example, Table A11 shows that the midscale and economy hotels that implement above-average price changes increase their revenue by 19.8%, compared with the 7.4% revenue increase by the below-average price change hotels. These findings validate the managerial and performance implications outlined in our framework.

We can also conduct a back-of-the-envelope calculation to quantify the impact of the regulation on hotels and show that the impact is sizable. For example, the pre-Airbnb law revenue for an NYC hotel with fewer than 75 rooms is $158.60 in 2013 dollars per available room per day in the preceding year. Our estimate shows that such a small hotel increases its revenue by 6.2% (total marginal effect from Table 2, Model 3), a $9.83 revenue increase per room per day. Assuming the hotels in this category have 40 rooms on average, this translates to a $144K revenue increase per hotel per year or a $18.2 million increase for the hotels per year in this small hotel category in our dataset. We can similarly calculate the impact of the regulation for all NYC hotels. Using the revenue increase of 3.53% (Table 2, Model 1) and the average pre-regulation revenue of $200.51, the total revenue increase for all the hotels per year is $285 million. This magnitude shows the importance of such a policy change on hotel performance.

5.3 Alternative Explanations

5.3.1 Presence of customer segments or self-sorting

One might argue that Airbnb targets leisure customers, while hotels target business travelers. Thus, they are not direct competitors. Also, due to the uncertain nature of the quality of lodging offered by Airbnb, risk-averse customers might self-select into hotels and never seek Airbnb accommodations. Therefore, the observed change in hotel revenue (or price or quality), which we attribute to the short-term rental regulation, is caused not by the ease of competitive pressure from Airbnb but by a different factor that is applicable only to hotel customers, such as the change in demand for business travelers seeking hotels in NYC relative to New Jersey that coincided with the timing of the short-term rental regulation.

While the presence of different customer segments is plausible, it does not fully explain our results. For example, the presence of different customer segments does not explain why we observe the increase in price only for resource-constrained hotels or the decrease in quality only for resource-rich hotels. Moreover, for all types of customers, the short-term rental regulation reduces the supply of Airbnb accommodations, making hotel accommodations relatively more attractive. If different customer segments explain our results, then it must be the case that business customers or risk-averse customers respond to price (or quality) more strongly than leisure customers or risk-neutral customers. We are not sure why that is the case.

5.3.2 Differences in regions

One might also argue that the NYC region is fundamentally different from the New Jersey region due to its higher number of tourist attractions and business centers. While such a difference must exist, we only need both regions to exhibit similar pre-trends, and our parallel trend test confirms this. We also control several factors to account for the difference between the two regions. Plus, we conduct several robustness tests, including matching NYC hotels to similar New Jersey hotels, testing market-specific trends, and incorporating Airbnb listing data. Results from these tests consistently reinforce that our main findings are not driven by regional differences.

5.4 Discussion

5.4.1 Asymmetry between when gig disruptors entered and restricted

In our context, an exogenous event results in an ease of competition from the gig disruptors.

However, one might wonder how incumbents respond when gig disruptors enter and whether the effect of an increase or decrease in competition is symmetric. While the fundamental problem of causal inference dictates that the counterfactual remains unobserved, the impact on incumbent performance is likely symmetric because the substitution effect is necessarily symmetric. Incumbents' price response is also likely symmetric because it is an adjustment that can be swiftly implemented from observing changes in occupancy, a direct result of the substitution effect. The only likely asymmetry thus comes from the quality response. As discussed, quality changes require time. Also, while better quality can serve as a response to increased competition, firms are less likely to reduce quality with decreased competition due to considerations of firm reputation. Hence, our quality response estimates lie in the conservative end of the spectrum.

5.4.2 Demand spillovers to New Jersey

One might also worry about the potential demand spillovers of lodging to the New Jersey areas proximate to Manhattan, especially after the Airbnb law that made hotels scarcer in NYC. While it is difficult to quantify whether or where such a spillover effect might occur, such a spillover effect is likely to be more pronounced in the "after" period, so it will only attenuate our results.

5.5 Conclusion

Our study has important implications for research on the impact of gig disruptors on incumbents. While we focus on the hotel industry, other industries such as taxi, newspaper, retail, business services, education, and physical labor face similar entry threats. Our theoretical arguments and empirical design can be extended to other contexts and provide new insight into the impact of such entries. For example, the entries of Uber and Lyft heavily impacted the operations of existing taxi cabs, the popularization of LinkedIn Learning reshaped the competitive landscape of educational companies, and the emergence of TaskRabbit drove many traditional labor services out of business. With challenges from these gig disruptors, incumbents must first discern the direction of the disruptions to form an effective response. While it is predicted that the resource-constrained incumbents will be more impacted by supply-side disruption, conditions vary concerning when the resource-rich incumbents should reallocate resources to raise customers' willingness to pay to respond to entries targeting niche markets. Ultimately, many of these industries consist of a heterogeneous set of firms, and our framework can help form an initial blueprint, if not the ultimate solution, for incumbents to respond in an effective manner.

Our study also has implications for managers and policymakers. We show that the short-term rental regulation has heterogeneous impacts on hotels, and resource-constrained hotels that raise their prices benefit more from the regulation. We also show that the impact of the regulation on hotel performance is sizable. These results show the importance of such a policy change in hotel performance and the benefits for the hotels that respond correctly.

This paper is not without limitations. First, a causal interpretation of our empirical results relies on the introduction of the short-term rental regulation being exogenous to hotel performance. We argue that this is a reasonable assumption given our empirical context of the hotel industry in the New York metropolitan area, where the exacerbating housing crisis has been widely linked to the rise of Airbnb. We also use Google Trends data to show a lack of anticipation of the regulation by most hotels and Airbnb hosts. Nevertheless, it is still possible that hotel-related reasons, such as lobbying efforts by certain hotel groups, might have influenced the legislation. In addition, while the New York State government vowed to increase enforcement efforts, non-compliance from the disruptors and their hosts remained non-negligible (Coles, Egesdal, Ellen, Li, & Sundararajan, 2018). While we show evidence that Airbnb's growth was clearly deterred after the regulation, such concerns can still impede the magnitude of estimations of our findings. Also, we focus primarily on regulation that dampens the effects of short-term rental disruptors that have already entered to compete. Hence, whether the findings, especially those pertaining to quality response, will similarly apply to disruptive entries that have yet to happen remains to be further examined. Therefore, researchers should be mindful of these limitations and interpret the results with some caution.

Notwithstanding the limitations, this paper makes important theoretical and empirical contributions to the literature on the gig and sharing economy, platform, and market entry. While issues remain to be addressed by future work, we believe this study represents an exciting step toward uncovering many opportunities in management research on incumbents' strategic responses to disruptions arising from new value propositions offered by emerging innovations.

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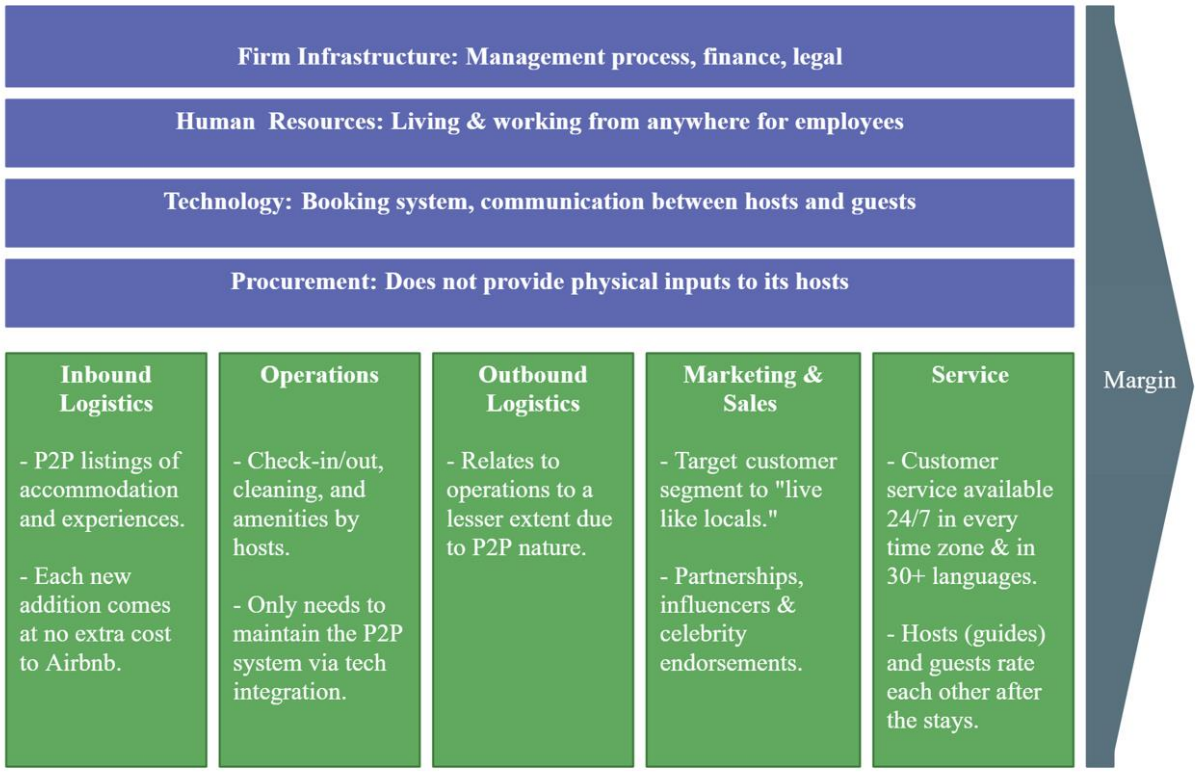


FIGURE 1 Airbnb’s value chain vs. hotels’ value chain

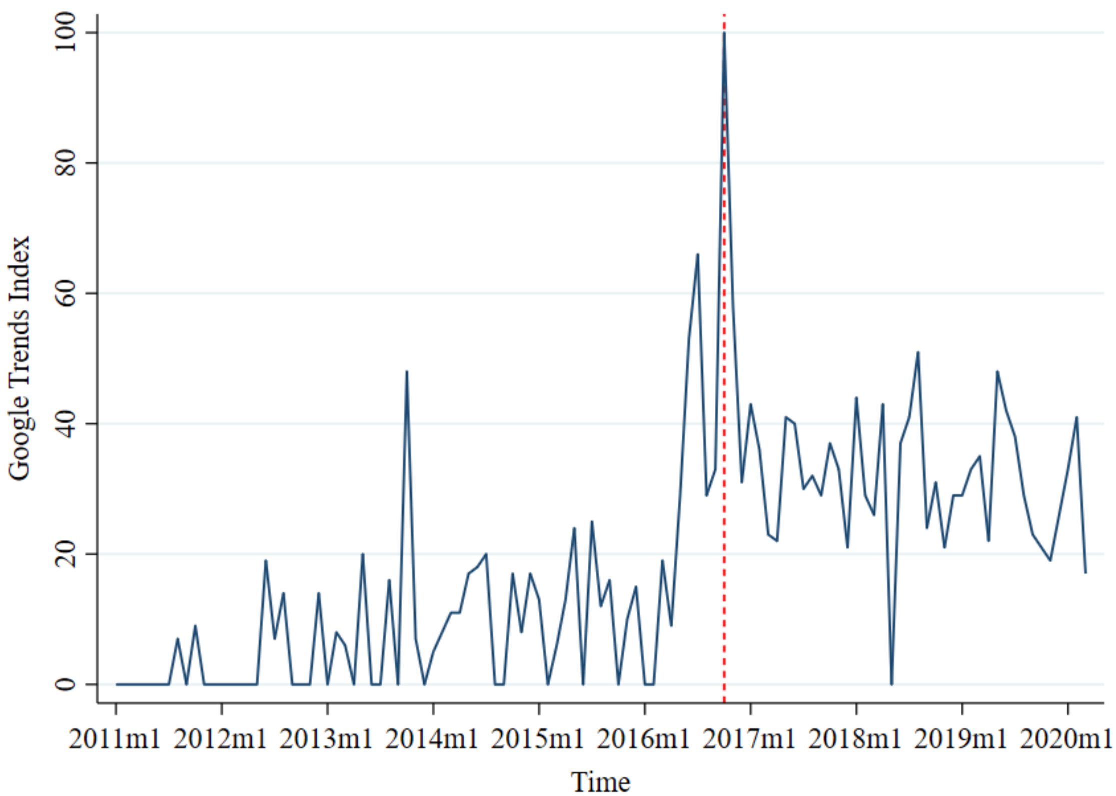
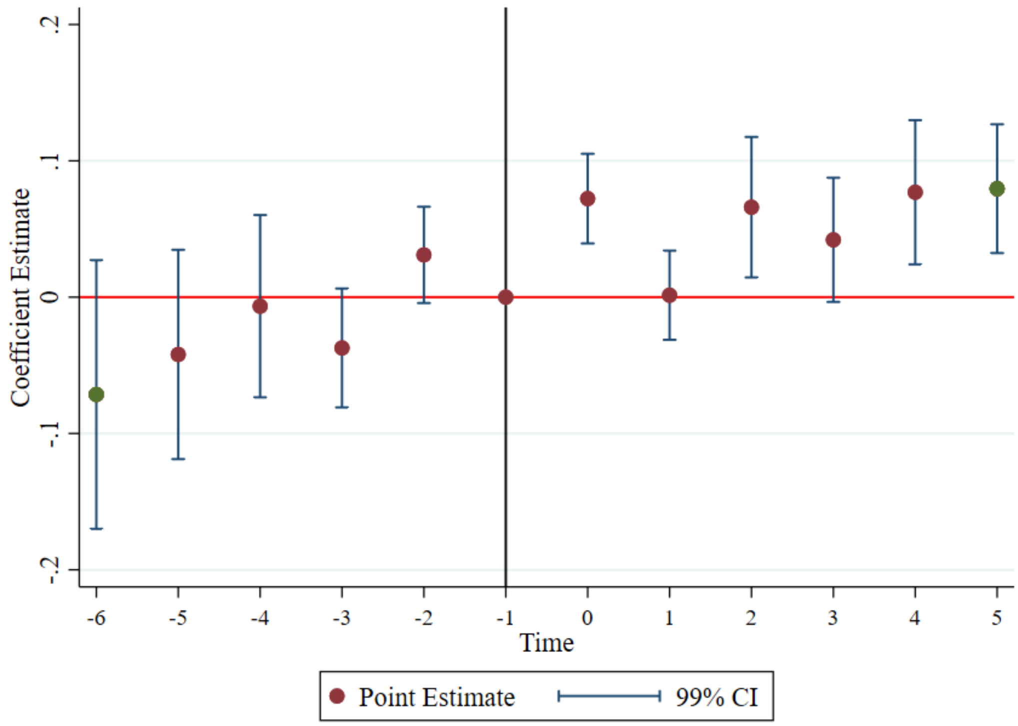


FIGURE 2 Search volume for Airbnb law in New York City



Note: Time periods grouped into half years for ease of presentation. Periods beyond 36 months are accumulated into final points. Data source: STR, LLC

FIGURE 3 Time-to-regulation effects on hotel revenue

TABLE 1 Summary statistics for selected variables

	New York City, NY			**Adjacent NJ Areas**		
Variable	**Count**	**Mean**	**SD**	**Count**	**Mean**	**SD**
Deflated revenue per available room in US dollars	33843	207.13	124.34	23709	81.07	35.53
Deflated average daily rate in US dollars	33843	244.78	155.51	23709	112.64	38.94
Hotel tracks food & beverage costs or not (annual)	924	0.75	0.43	612	0.68	0.47
Hotel operation (1–3 scale; chain to independent)	33843	2.21	0.73	23709	1.91	0.48
Hotel class (1–6 scale; luxury to economy)	33843	3.04	1.45	23709	3.90	1.34
Hotel location (1–4 scale; urban to small town)	33843	1.21	0.61	23709	1.86	0.61
Hotel size (1–5 scale; <75 rooms to >500 rooms)	33843	2.56	1.17	23709	2.33	0.81
Hotel open year	33843	1990	34.86	23709	1991	18.06
Unemployment rate (%)	33843	5.39	1.60	23709	5.34	1.62
Number of hotels in the same market	33843	454.83	45.47	23709	105.04	26.84

The breakdown of the numerical scales of hotel property characteristics is the following:
Hotel operation (1 = chain owned and/or managed, 2 = franchised, 3 = independent)
Hotel class (1 = luxury, 2 = upper upscale, 3 = upscale, 4 = upper midscale, 5 = midscale, 6 = economy)
Hotel location (1 = urban, 2 = suburban, 3 = airport, 4 = small metro/town)
Hotel size (1 = less than 75 rooms, 2 = 75–149 rooms, 3 = 150–299 rooms, 4 = 300–500 rooms, 5 = greater than 500 rooms)
Markets include New York City, and Bergen-Passaic, Newark, and Central New Jersey in New Jersey.
Revenue and price are in 2013 US dollars. Data source: STR, LLC.

TABLE 2 Performance impact on incumbent hotels (DV: Log of revenue per hotel room)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.0353**	-0.0103	-0.165***	0.0389+
	(0.0131)	(0.0636)	(0.0423)	(0.0211)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		0.0641		
		(0.0670)		
Upscale		0.0330		
		(0.0685)		
Upper midscale		0.0309		
		(0.0680)		
Midscale		0.0144		
		(0.0842)		
Economy		0.155+		
		(0.0870)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.169**	
			(0.0586)	
150–299 rooms			0.194***	
			(0.0466)	
75–149 rooms			0.210***	
			(0.0471)	
<75 rooms			0.227***	
			(0.0547)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				0.0589
				(0.0827)
Airport				0.106*
				(0.0471)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	57,552	57,552	57,552	57,552
R^2	0.803	0.805	0.804	0.804
F	36.41	22.63	27.27	99.17

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE 3 Price response by incumbent hotels (DV: Log of hotel average daily rate)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	-0.0115	0.0722	-0.103*	-0.00222
	(0.00740)	(0.0577)	(0.0412)	(0.0125)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		-0.0932		
		(0.0595)		
Upscale		-0.116+		
		(0.0602)		
Upper midscale		-0.101+		
		(0.0596)		
Midscale		-0.0965		
		(0.0657)		
Economy		0.0552		
		(0.0725)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.0561	
			(0.0470)	
150–299 rooms			0.0710	
			(0.0436)	
75–149 rooms			0.0947*	
			(0.0432)	
<75 rooms			0.151**	
			(0.0487)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				-0.0337
				(0.0304)
Airport				0.108***
				(0.0299)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	57,552	57,552	57,552	57,552
R^2	0.855	0.857	0.856	0.856
F	47.24	30.16	32.19	102.5

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE 4 Service response by incumbent hotels (DV: Hotel tracks food & beverage costs)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.0221	0.0325	0.188*	0.132+
	(0.0381)	(0.0395)	(0.0859)	(0.0789)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Economy as base)				
Midscale		-0.172		
		(0.118)		
Upper midscale		0.0314		
		(0.156)		
Upscale		-0.0419		
		(0.0516)		
Upper upscale		-0.0350		
		(0.0450)		
Luxury		-0.0196		
		(0.0501)		
NY×After Airbnb Law×Hotel size (75–149 rooms as base)				
150–299 rooms			-0.236*	
			(0.100)	
300–500 rooms			-0.242**	
			(0.0933)	
>500 rooms			-0.150+	
			(0.0840)	
NY×After Airbnb Law×Hotel location (Airport as base)				
Urban				-0.137
				(0.0894)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	1,536	1,536	1,536	1,536
R^2	0.635	0.645	0.645	0.636
F	40.20	23.94	32.22	31.57

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

ONLINE APPENDIX

TABLE A1 Performance impact on incumbent hotels, CEM matched sample
(DV: Log of revenue per hotel room)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.0936*	0.0787	-0.122	0.0630
	(0.0462)	(0.0784)	(0.0862)	(0.0396)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		0.0766*		
		(0.0379)		
Upscale		-0.0272		
		(0.0960)		
Upper midscale		-0.0872		
		(0.134)		
Midscale		0.225***		
		(0.0679)		
Economy		0.207**		
		(0.0702)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.0950	
			(0.130)	
150–299 rooms			0.201***	
			(0.0508)	
75–149 rooms			0.212	
			(0.143)	
<75 rooms			0.336***	
			(0.0572)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				0.162
				(0.247)
Airport				0.220**
				(0.0780)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	33,523	33,523	33,523	33,523
R^2	0.747	0.751	0.752	0.752
F	31.58	23.26	43.59	88.55

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Estimates are run using a smaller matched sample that reconstructs the treatment group into the control group using the CEM method by identifying "clones" of the NYC and NJ hotels based on major observable characteristics, including class, size, and location. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A2 Price response by incumbent hotels, CEM matched sample
(DV: Log of hotel average daily rate)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.0151	-0.0143	-0.129***	0.000931
	(0.0179)	(0.0216)	(0.0221)	(0.0187)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		0.0444+		
		(0.0266)		
Upscale		-0.0270		
		(0.0490)		
Upper midscale		0.0210		
		(0.0460)		
Midscale		0.0461		
		(0.0410)		
Economy		0.173***		
		(0.0500)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.0780	
			(0.0597)	
150–299 rooms			0.120***	
			(0.0265)	
75–149 rooms			0.187***	
			(0.0443)	
<75 rooms			0.159***	
			(0.0326)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				0.0534
				(0.120)
Airport				0.106**
				(0.0375)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	33523	33523	33523	33523
R^2	0.850	0.852	0.851	0.851
F	56.48	39.68	54.24	102.5

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Estimates are run using a smaller matched sample that reconstructs the treatment group into the control group using the CEM method by identifying "clones" of the NYC and NJ hotels based on major observable characteristics, including class, size, and location. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A3 Service response by incumbent hotels, CEM matched sample
(DV: Hotel tracks food & beverage costs)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.0546	0.0516	0.310*	0.390*
	(0.0433)	(0.0382)	(0.149)	(0.158)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Economy as base)				
Upper midscale		-0.00631		
		(0.203)		
Upscale		0.0232		
		(0.0629)		
Upper upscale		-0.0662		
		(0.0415)		
Luxury		-0.00100		
		(0.0464)		
NY×After Airbnb Law×Hotel size (75–149 rooms as base)				
150–299 rooms			-0.280+	
			(0.161)	
300–500 rooms			-0.359*	
			(0.155)	
>500 rooms			-0.214	
			(0.161)	
NY×After Airbnb Law×Hotel location (Airport as base)				
Urban				-0.341*
				(0.160)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	815	815	815	815
R^2	0.661	0.674	0.669	0.662
F	1.349	N/A	1.148	1.392

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Estimates are run using a smaller matched sample that reconstructs the treatment group into the control group using the CEM method by identifying "clones" of the NYC and NJ hotels based on major observable characteristics, including class, size, and location. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A4 Performance impact on incumbent hotels, with linear market-specific trends (DV: Log of revenue per hotel room)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.138***	0.111+	-0.0385	0.129***
	(0.0123)	(0.0628)	(0.0448)	(0.0248)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		0.0477		
		(0.0664)		
Upscale		0.0120		
		(0.0676)		
Upper midscale		0.0121		
		(0.0678)		
Midscale		-0.00399		
		(0.0836)		
Economy		0.129		
		(0.0864)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.145*	
			(0.0592)	
150–299 rooms			0.172***	
			(0.0470)	
75–149 rooms			0.184***	
			(0.0501)	
<75 rooms			0.203***	
			(0.0558)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				0.0612
				(0.0830)
Airport				0.145**
				(0.0551)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	57,552	57,552	57,552	57,552
R^2	0.804	0.807	0.805	0.805
F	49.00	27.76	32.05	103.2

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. The inclusion of linear market-specific trends takes the form of market×continuous time to capture the possibility that factors influencing gig disruptors and hotels might vary within a market over time and confound the estimates of market fixed effects. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A5 Price response by incumbent hotels, with linear market-specific trends (DV: Log of hotel average daily rate)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.102***	0.193**	0.0194	0.109***
	(0.00683)	(0.0627)	(0.0416)	(0.0134)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		-0.101		
		(0.0645)		
Upscale		-0.125+		
		(0.0650)		
Upper midscale		-0.109+		
		(0.0646)		
Midscale		-0.106		
		(0.0701)		
Economy		0.0410		
		(0.0764)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.0476	
			(0.0471)	
150–299 rooms			0.0637	
			(0.0433)	
75–149 rooms			0.0856*	
			(0.0434)	
<75 rooms			0.140**	
			(0.0485)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				-0.0431
				(0.0303)
Airport				0.118***
				(0.0314)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	57,552	57,552	57,552	57,552
R^2	0.857	0.859	0.857	0.858
F	85.63	47.83	52.11	117.0

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. The inclusion of linear market-specific trends takes the form of market×continuous time to capture the possibility that factors influencing gig disruptors and hotels might vary within a market over time and confound the estimates of market fixed effects. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A6 Service response by incumbent hotels, with linear market-specific trends (DV: Hotel tracks food & beverage costs)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.0302	0.0517	0.198*	0.146+
	(0.0385)	(0.0471)	(0.0859)	(0.0854)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Economy as base)				
Midscale		-0.168		
		(0.119)		
Upper midscale		0.0261		
		(0.160)		
Upscale		-0.0458		
		(0.0521)		
Upper upscale		-0.0377		
		(0.0477)		
Luxury		-0.0111		
		(0.0526)		
NY×After Airbnb Law×Hotel size (75–149 rooms as base)				
150–299 rooms			-0.235*	
			(0.100)	
300–500 rooms			-0.243*	
			(0.0938)	
>500 rooms			-0.153+	
			(0.0884)	
NY×After Airbnb Law×Hotel location (Airport as base)				
Urban				-0.154
				(0.0991)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	1,536	1,536	1,536	1,536
R^2	0.636	0.645	0.645	0.636
F	40.06	23.52	32.05	31.67

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. The inclusion of linear market-specific trends takes the form of market×continuous time to capture the possibility that factors influencing gig disruptors and hotels might vary within a market over time and confound the estimates of market fixed effects. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A7 DID analyses for Airbnb growth (11 pre & 37 post monthly periods)
(DV: Log of # of Airbnb listings)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	-0.319***	-0.320***	-0.0239***	-0.0240***
	(0.00165)	(0.000938)	(0.000291)	(0.000297)
NY	2.585***	N/A	N/A	N/A
	(0.00101)			
After Airbnb Law	0.593***	N/A	N/A	N/A
	(0.00165)			
Constant	7.862***	9.933***	9.788***	9.788***
	(0.00101)	(0.000510)	(0.000182)	(0.000185)
State FE	No	Yes	Yes	Yes
Year and month FE	No	Yes	Yes	Yes
State-specific trends, linear	No	No	Yes	Yes
State-specific trends, quadratic	No	No	No	Yes
Observations	37,214	37,214	37,214	37,214
R^2	0.982	0.996	0.999	0.999
F	N/A	116223.7	6744.2	6501.4

Robust standard errors clustered by market location are reported in parentheses. Model 1 estimates the most parsimonious DID form. Model 2 includes state fixed effects that account for constant differences between states and time fixed effects that account for unobserved heterogeneity that change over time but not between states. Model 3 also adds linear state-specific trends that account for factors that evolve linearly within a state over time. Model 4 further includes quadratic state-specific trends that account for factors that evolve non-linearly within a state over time. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: Inside Airbnb.

TABLE A8 Performance impact on incumbent hotels, with Airbnb control
(DV: Log of revenue per hotel rooms)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	0.0391+	-0.0398	-0.116**	0.0383**
	(0.0137)	(0.0174)	(0.00987)	(0.00503)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		0.105**		
		(0.0107)		
Upscale		0.0662*		
		(0.0138)		
Upper midscale		0.0897**		
		(0.0137)		
Midscale		0.0540		
		(0.0239)		
Economy		0.115***		
		(0.00627)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.120*	
			(0.0233)	
150–299 rooms			0.150***	
			(0.00789)	
75–149 rooms			0.169***	
			(0.0106)	
<75 rooms			0.150**	
			(0.0181)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				-0.409***
				(0.0123)
Airport				-0.000429
				(0.00600)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	34,724	34,724	34,724	34,724
R^2	0.804	0.807	0.804	0.805
F	N/A	N/A	N/A	N/A

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. All models are estimated using a shortened timeframe during which we have the numbers of Airbnb listings available and included as a covariate in a logarithmic form to account for the influences of non-compliant Airbnb hosts. Estimates with Airbnb listings included in non-logarithmic form yield similar results. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by market location are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A9 Price response by incumbent hotels, with Airbnb control
(DV: Log of hotel average daily rate)

	Model 1	**Model 2**	**Model 3**	**Model 4**
NY×After Airbnb Law	-0.0379**	-0.0387	-0.0920***	-0.0347***
	(0.00627)	(0.0177)	(0.00105)	(0.00181)
Selected interaction terms:				
NY×After Airbnb Law×Hotel class (Luxury as base)				
Upper upscale		0.00584		
		(0.0270)		
Upscale		-0.0179		
		(0.0115)		
Upper midscale		-0.000558		
		(0.0257)		
Midscale		-0.0207		
		(0.0375)		
Economy		0.0734		
		(0.0329)		
NY×After Airbnb Law×Hotel size (>500 rooms as base)				
300–500 rooms			0.0458*	
			(0.00978)	
150–299 rooms			0.0396**	
			(0.00366)	
75–149 rooms			0.0552**	
			(0.00576)	
<75 rooms			0.0719*	
			(0.0152)	
NY×After Airbnb Law×Hotel location (Urban as base)				
Suburban				-0.286***
				(0.00700)
Airport				0.0431***
				(0.00204)
Hotel chain FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes
Observations	34,724	34,724	34,724	34,724
R^2	0.852	0.854	0.852	0.852
F	N/A	N/A	N/A	N/A

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. All models are estimated using a shortened timeframe during which we have the numbers of Airbnb listings available and included as a covariate in a logarithmic form to account for the influences of non-compliant Airbnb hosts. Estimates with Airbnb listings included in non-logarithmic form yield similar results. Other interaction terms such as NY×Hotel info and After Airbnb Law×Hotel info are suppressed for ease of presentation. Robust standard errors clustered by market location are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A10 Performance impact, above/below average price change, interaction with hotel class (DV: Log of revenue per hotel room)

	Above average price change	**Below average price change**
NY×After Airbnb Law	0.0450	0.0665**
	(0.0294)	(0.0244)
Selected interaction terms:		
NY×After Airbnb Law×Hotel class (Luxury & Upper upscale as base)		
Upscale & Upper midscale	0.0630	-0.0154
	(0.0427)	(0.0315)
Midscale & Economy	0.188**	-0.00404
	(0.0629)	(0.0430)
Hotel chain FE	Yes	Yes
Market FE	Yes	Yes
Year and month FE	Yes	Yes
Observations	25,676	25,981
R^2	0.844	0.803
F	10.42	15.33

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Other interaction terms such as NY×Hotel class and After Airbnb Law×Hotel class are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A11 Performance impact, above/below average price change, midscale & economy hotels only (DV: Log of revenue per hotel room)

	Above average price change	**Below average price change**
NY×After Airbnb Law	0.198***	0.0738*
	(0.0500)	(0.0345)
Hotel chain FE	Yes	Yes
Market FE	Yes	Yes
Year and month FE	Yes	Yes
Observations	5,941	3,852
R^2	0.778	0.798
F	11.85	28.53

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A12 Performance impact, above/below average price change, interaction with hotel size (DV: Log of revenue per hotel room)

	Above average price change	**Below average price change**
NY×After Airbnb Law	0.0290	0.0483+
	(0.0453)	(0.0249)
Selected interaction terms:		
NY×After Airbnb Law×Hotel size (>300 Rooms as base)		
150–299 rooms	0.0440	0.0311
	(0.0527)	(0.0398)
75–149 rooms	0.0332	0.0328
	(0.0554)	(0.0350)
<75 rooms	0.157*	-0.0948+
	(0.0655)	(0.0500)
Hotel chain FE	Yes	Yes
Market FE	Yes	Yes
Year and month FE	Yes	Yes
Observations	25,676	25,981
R^2	0.850	0.816
F	20.79	115.0

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Other interaction terms such as NY×Hotel size and After Airbnb Law×Hotel size are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A13 Performance impact, above/below average price change, < 75-room hotels only (DV: Log of revenue per hotel room)

	Above average price change	**Below average price change**
NY×After Airbnb Law	0.187**	0.0409
	(0.0542)	(0.0378)
Hotel chain FE	Yes	Yes
Market FE	Yes	Yes
Year and month FE	Yes	Yes
Observations	4,415	3,362
R^2	0.841	0.775
F	N/A	36.40

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A14 Performance impact, above/below average price change, interaction with hotel location (DV: Log of revenue per hotel room)

	Above average price change	Below average price change
NY×After Airbnb Law	0.0793**	0.0691***
	(0.0256)	(0.0201)
Selected interaction terms:		
NY×After Airbnb Law×Hotel location (Urban as base)		
Suburban, Airport, & Small Metro	0.124*	0.0743
	(0.0526)	(0.0502)
Hotel chain FE	Yes	Yes
Market FE	Yes	Yes
Year and month FE	Yes	Yes
Observations	25,676	25,981
R^2	0.847	0.815
F	29.32	163.9

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Other interaction terms such as NY×Hotel location and After Airbnb Law×Hotel location are suppressed for ease of presentation. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.

TABLE A15 Performance impact, above/below average price change, suburban, airport & small metro hotels only (DV: Log of revenue per hotel room)

	Above average price change	Below average price change
NY×After Airbnb Law	0.212***	0.154***
	(0.0484)	(0.0383)
Hotel chain FE	Yes	Yes
Market FE	Yes	Yes
Year and month FE	Yes	Yes
Observations	13,855	5,287
R^2	0.770	0.807
F	5.732	26.52

Controls include hotel class, location, size, operation mode, open year, competition density, and unemployment rate. Robust standard errors clustered by hotel ID are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$
Data source: STR, LLC.