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# Blessing in Disguise? Environmental Shocks and Performance Enhancement


## Abstract

This paper studies how hotels and their guests respond to exogenous detrimental environmental shocks. We employ a unique dataset of online reviews covering all the hotels in Singapore and Hong Kong from three prominent hotel-booking platforms. The results show that the review scores of hotels in Singapore dropped sharply by up to 0.35 points during the haze periods and reverted immediately to and exceeded eventually their previous level after the haze shock. We discuss possible explanations for the observed effects, including hotels' service quality, managers' efforts and guests' mood. Negative environmental shocks motivate managers to reflect on their operating efficiency, and active communication on online travel reviews prompts reflection and service improvements. At the same time, large-scale improvement in service quality is not persistent and increases at a decreasing rate during subsequent environmental shocks. Our findings shed light on the importance of realizing deficiencies on management and operation in the presence of negative shocks and contribute to a growing literature on environment, interruption, and management at the micro level.



**Keywords:** Air pollution, Productivity, Performance, Tourism, Information and Learning

**JEL Code:** Q51, Q53, Z30, D83, D22

# 1 Introduction

*"The goal as a company is to have customer service that is not just the best, but legendary."*
by Sam Walton (1918-1992), Founder of Wal-Mart Stores Inc.

With the increasing importance and share of the service sector (69%) in the global economies (World Bank, 2017), providing superior services and products has become a priority for many businesses. With a growing focus on the consumer experience, it is vital for firms to provide the best services while maintaining their peak productivity in order to remain competitive in the marketplace. Moreover, it is important for customers to maximize utility when choosing services and products. In this paper, we use data collected from large online review platforms to demonstrate that negative reviews caused by environmental shocks help firms in the hospitality industry to provide high quality services and maintain a high level of productivity. In addition, we explore why firms optimize their performance only when they are prompted by negative shocks.

In this paper, we focus on an exogenous weather shock, which impacts the firms' reputations differently from any other event or circumstance as it is unrelated to inefficient management or under-performance. We present evidence to show that exogenous weather shocks indirectly affect firms' online reputation as weather directly influences the consumer's mood and experience. This means that an exogenous weather shock can lead to a lower level of consumer satisfaction that is unrelated to the quality of services or products. We further test whether externalities caused by air pollution lead hotels to pay greater attention to improving their service. In addition, we look at how pollution impacts the service sectors by directly affecting consumers' willingness to pay and by indirectly affecting firms' productivity.

We develop crawlers using the Python language to auto-parse the web pages and collect a large dataset of online hotel reviews of all the hotels in Singapore and Hong Kong between June 2012 and December 2016 from three prominent hotel-booking websites: *TripAdvisor*, *Agoda*, and *Expedia*. Previous research has focused on the traditional manufacturing industry and neglected the service sector, whose productivity has been challenging to measure due to difficulties in quantifying the inputs and outputs (Grönroos and Ojasalo, 2004). With the rapid development of information technology and e-commerce (Avery et al., 1999; Chevalier and Mayzlin, 2006; Chen and Xie, 2008; Vermeulen and Seegers, 2009; Liu and Park, 2015), it is widely accepted that online reviews efficiently measure consumers' perceived evaluations of products and their own subjective well-being related to services (Ba and Pavlou, 2002; Chevalier and Mayzlin, 2006; Duan et al., 2008; Mudambi and Schuff, 2010)[1]. The existing

[1]A great deal of literature has thoroughly documented the importance of online review or electronic

studies on hotels also show that online reviews, especially negative reviews, can inform hotel managers about their guests' satisfaction with the services provided during their stay, helping managers to identify areas that require improvement (Vermeulen and Seegers, 2009; Chaves et al., 2012). During haze episodes, travellers experiencing the ill effects of air pollution may post a negative review of the hotel even if the hotel maintains a high quality of services.

The haze episodes occurred in Singapore from 2012 to 2016 provide us an ideal opportunity to examine the dynamic responses of travellers and hoteliers to environmental shocks. First, the haze episode in Singapore is purely random and exogenous because the air pollutants originate from Indonesia and depend on wind direction (Sheldon and Sankaran, 2017). Moreover, as Singapore is a small island spanning 709 square kilometers, air pollution is homogeneously spread island-wide, which means everyone in Singapore is exposed to the air pollutants, especially when the Pollutants Standards Index (PSI) reading is over 300[2]. Therefore, the potential bias due to endogeneity and sorting in the existing pollution studies (Dominici et al., 2014) are unlikely to be concerns in quantifying the impact of air pollution on travellers' subjective well-being in our paper.

Second, we include Hong Kong as a control group because Hong Kong and Singapore share strong similarities in geographical, economic, and cultural aspects. However, unlike Singapore, Hong Kong is free of severe haze, with a relatively stable monthly PSI mean value that is lower than 50 during the sample period. This allows us to use a difference-in-differences approach to examine the responses of travellers and hoteliers during and after the haze episode.

Third, the rich information on the review contents enables us to explore the underlying mechanisms that drive the effect of haze on the review score. For instance, using information on the subcategory review scores on six aspects of the accommodation experience, including *cleanliness, service, location, sleep, value,* and *room*, we define the improvable (*cleanliness*, *service*, and *value*) and non-improvable (*location* and *room*) categories of hotel service and investigate which category is responsive to the haze shock.

In this paper, we focus on four areas of interest. First, we examine whether the review score provided by guests travelling in Singapore drops during the haze episode. If so, we identify the category of hotel service (improvable or non-improvable) with the lower score. More specifically, a lower score for the improvable category suggests that the quality of hotel services is the reason for the guests' dissatisfaction, whereas a lower score for the non-improvable category indicates that the mood might give rise to the negative reviews. Second, we look at whether the review score rises after the haze episode. If so, we identify the

word of mouth (eWOM) in relation to sales (Chevalier and Mayzlin, 2006; Duan et al., 2008), trust (Ba and Pavlou, 2002), and consumer decision-making (Mudambi and Schuff, 2010).

[2]The haze causes irritation to eyes and, when inhaled for prolonged periods, can have harmful long-term effects on the lungs, heart, and respiratory system (Jayachandran, 2009).

category of hotel service with the higher score. A significantly higher score for the improvable category after the haze episode implies that hotels only provide the better quality services when they are prompted by negative reputation shocks. Third, we determine whether the change in the review score after the haze episode persists in the long run. Fourth, we estimate the welfare gains and losses for guests staying in Singapore during the haze episode and for guests staying after the haze episode.

Specifically, we combine the online review data with monthly weather data in Singapore and Hong Kong. We begin the analysis by identifying a causal relationship between weather shocks and online review scores. We find a temporary decrease of 0.27 to 0.35 points in hotel online review scores during the haze period and an average increase of approximately 0.23 points after the haze shock. An analysis of the subcategory online review scores shows that air pollution affects the consumption mood rather than the quality of hotel services because scores of the improvable categories such as *cleanliness* and *service* barely change, while scores of the non-improvable categories such as *location* decline substantially during the haze episode. Moreover, the scores of the improvable categories increase by 0.25 points on average after the haze shock compared to their previous levels, whereas the scores of the non-improvable categories revert to their original levels. Using difference-in-differences and triple-differences approaches that rely on the subcategory review scores and reviews from two regions, we show that, following a temporary reputation crisis due to a negative environmental shock, hoteliers largely improve their operations and services in order to restore their online image and retain customers.

Furthermore, we examine the underlying mechanisms of the ex-post improvement of online review scores by studying behavioral changes from the hotels' perspective. The results indicate that negative environmental shocks and online reviews prompt managers to reflect on their operating efficiency and improve their services, suggesting that a sizable share of hotels operate at a sub-optimal level and hotels have the capacity to improve their services and online reputation. In particular, hotels with managers closely monitor online reviews and respond to negative reviews show significant improvement. We also find heterogeneity of responses across types of traveller, continents of origin, and hotel star ratings. Lastly, we conduct a welfare analysis and show that tourists in Singapore on average enjoy a service improvement estimated at S$5.67 per room per night (S$70 million in total) in the subsequent 12 months following a haze shock. Moreover, we rule out four alternative explanations for the increases on review scores after haze shocks, including unobserved hotel-level shocks, changes in the hotel sample, changes of customer quality, and outliers in the responses. Our results survive a battery of robustness tests and falsification tests.

Our paper links to the existing literature along three dimensions. First, our paper contributes to the understanding of economic consequences of interruption. On the one hand, researchers have revealed the negative consequences of interruption in workplace (Herrmann and Rockoff, 2012; Coviello et al., 2014; Cai et al., 2017). Recent work by Cai et al. (2017) estimate the impact of machine-breakdown on workers' productivity when the machine is fixed by using worker-level daily data from a plastics-printing company in China. They find a 3.3% decrease in the worker's productivity ex-post the exogenous interruption. On the other hand, some studies have provided eye-catching evidence to show how positive outcomes can be triggered by negative shocks. The most recent study by Larcom et al. (2017) documents the finding that a significant portion of commuters in London does not optimize their transportation route. The people who live around the underground train lines that underwent a 48-hour strike now save 20 seconds per journey after the exogenous strike because they were forced by the strike to choose a new route that turned out to be better. Hornbeck and Keniston (2017) focus on the effect of a disastrous event, which is the exogenous Boston fire, on urban growth. Their paper shows that the Boston fire created an opportunity for people to realize the constraints on urban growth. The results show that the values of lands in the burned areas and nearby un-burned areas increased enormously after the event, indicating that the fire brought positive outcomes because higher value buildings were constructed on the burned plots. Aggarwal et al. (2012) utilize private data on blog posting and readership from a Fortune 500 IT firm to study the effect of negative posts on blog readership. Their results show that negative posts trigger positive outcomes in the readership of an employee blog.

To the best of our knowledge, our study is the first that provides empirical evidence of how a detrimental environmental shock can spur service sector productivity. The results highlight the firms' ability to achieve higher productivity and provide better service quality in the service sectors. By exploring the persistency and dynamic path of the improvements, we show that substantial improvements are temporary, which is consistent with the theoretical analysis indicating that agents tend to satisfy rather than optimize, suggesting that they cease their efforts once they reach a satisfactory utility-level (Simon, 1955). Our study explores the reasons behind firms' decision to operate at a sub-optimal level in the absence of negative shocks, and identifies the ways in which firms can maintain their highest level of performance.

Second, this paper adds to the literature that addresses the issue of air pollution. Studies have found that the effect of particulates on the lungs can be increased through the absorption of certain chemicals linked to pulmonary cancer and hyperactivity in children (Jayachandran, 2009). Research by Dominici et al. (2014) supports a moderate association between pollutant levels and respiratory discomfort and related illnesses, such as eye irritation. Moreover, health related research documents the causal relationship between exposure to air pollution and depression, anxiety, tension, and anger (Evans et al., 1987), which may adversely affect economic outcomes (Hirshleifer and Shumway, 2003; Levy and Yagil, 2011). Poor air conditions have not only increased health concerns over the past two decades, but also lead to behavioral responses, such as labor supply and labor productivity (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Chang et al., 2016), defensive investments (Deschênes et al., 2017), housing market dynamics (Chay and Greenstone, 2003), and avoidance behavior (Zivin and Neidell, 2009).

Our study examines the negative environmental externality from a new angle. While previous studies focus on the detrimental effects of environmental shocks and their overall economic impact or health related consequences, this paper not only focuses on the negative effects of weather shocks, but also highlights the positive consequences after the weather shocks. Adding to the existing literature on the relationship between psychological factors and pollution, the subcategory review score analysis provides further evidence on how pollution affects the mood of consumers and contributes to a decrease in consumer satisfaction in non-improvable service areas, such as *room* and *location*. The results reveal that, in the absence of negative exogenous shocks, hoteliers neglect areas that require improvement, which can lead to negative reviews. To assess and mitigate threats to their hotel's reputation, hoteliers should implement various channels to help them monitor the quality of their services at all times.

Third, our research is also related to the broader area of user-generated online reviews. This strand of literature explains the meaning of review scores from both the reviewer side and the organization side, helping us to better understand our results. Our paper looks at the role of review scores from the reviewers' perspective. Marketing literature has well documented the extent to which online review contents directly reflect reviewers' perception of the quality of the product or service (Hennig-Thurau et al., 2004; Bansal et al., 2005). Bansal et al. (2005) suggest that electronic word of mouth (eWOM) presented by other consumers online is extremely important for those experiential products, which provide consumers with indirect and sensory experience rather than goods with tangible traits. Some empirical papers have documented the impact of eWOM on sales (Chevalier and Mayzlin, 2006; Duan et al., 2008), trust (Ba and Pavlou, 2002), and consumer decision-making (Vermeulen and Seegers, 2009). The studies show that online review scores from hotel-booking platforms can be used to proxy the reviewers' evaluations of the tangible and intangible aspects of hotel services, allowing us to examine how the supply side and demand side of the service sector respond dynamically to environmental shocks as well as to identify the underlying mechanisms driving the changes.

Organizations have reasons to pay close attention to online reviews. As suggested in previous literature, eWOM exerts great influence on trust, decision-making, and sales. (Ba and Pavlou, 2002; Chevalier and Mayzlin, 2006; Duan et al., 2008; Vermeulen and Seegers, 2009). It can be considered as a way to reduce the information asymmetry for other consumers (Liu and Park, 2015). Thus, organizations and managers should be concerned about the content of their online reviews and review scores. Moreover, negative reviews are more important to managers than positive ones when it comes to first-time consumers (Mizerski, 1982). According to the economic theory and risk preference, first-time consumers tend to have higher risk-aversion, and negative reviews collide with their purchasing intention (Holt and Laury, 2002; Thompson, 2005). Thus, a negative review will collide with consumers' attitude and purchasing intention, implying that organizations should pay more attention to the negative comments than to the positive reviews (Cheema and Papatla, 2010). Also, organizations are aware that negative reviews can hurt their reputations, which subsequently causes customer churn and performance loss (Roberts and Dowling, 2002; Boyd et al., 2010). To repair the damage caused by negative reviews and address the potential service deficiency, managers should respond actively to negative reviews. Our analysis presents the links and mechanisms that help to explain why managers respond to negative reviews and why hotels improve their service quality.

The remainder of this paper is structured as follows. We start by providing background information on the air pollution in Southeast Asia and its general impact on surrounding economics, as well as the prevalence of online review in hotel industry in Section 2. Section 3 describes our dataset and descriptive statistics. Section 4 provides a conceptual framework to illustrate our research setting. Section 5 presents the reduced form evidence, including the analysis of the causal relationship between the negative environmental shock on hotel online reputation, the reputation and performance relationship, the reasons for sub-optimal performance, and the mechanism underlying the main effects. Section 6 discusses several alternative explanations and Section 7 conducts additional heterogeneity and falsification tests. Section 8 provides welfare analysis and Section 9 concludes.

# 2 Background

## 2.1 Wildfires in Southeast Asia and Haze Pollution in Singapore

In recent years, heat waves, droughts, and climate changes such as El Niño have led to big fires in several parts of the world, including the western United States, western Canada, the Amazon in South America, and Southeast Asia. Damage from fires has been a major factor in most cases, and has contributed to the high rate of deforestation. Fires are consuming millions of hectares of forest around the world, costing billions of dollars to fight and causing deaths and extensive destruction of property as well as environment. Many wildfires occur during periods of high temperatures and drought, but human activity has also made fire events more frequent and more intense. In particular, intentional burning for forest cultivation and agriculture has increased fire incidences in tropical areas.

In the ASEAN region, nearly all of the fires and haze over the past two decades have been caused directly by human intervention rather than by natural events (Qadri, 2001). For example, farmers and owners of agricultural land in Southeast Asia have for many years used burning as a way to clear land for agriculture, even though it is illegal. This method has been a primary cause of huge wildfires in the Indonesian archipelago. Prevailing winds blow smoke, ash, toxic gases and other pollutants from this area to nearby countries, such as Singapore and Malaysia.

The 1997 heat haze event experienced by Singapore, when the 24-hour Pollution Standard Index (PSI) reached the "unhealthy" level of 138,[3], was the first to receive international attention. During the event of 2013, a new record was set when the three-hour PSI reached 401, which is considerably higher than the threshold set for the "hazardous" level (Sheldon and Sankaran, 2017). However, the worst haze event in Singapore to date was that of October 2015, when the one-hour PSI reading reached 471 (NEA Singapore, 2016). The haze causes irritation to eyes and, when inhaled for prolonged periods, can have harmful long-term effects on the lungs, heart, and respiratory system (Jayachandran, 2009). Since haze pollutant contains carbon dioxide and sulfur dioxide, along with aerosols and toxic particulates as well as a strong acrid and burning smell, it is easily detectable by public, and the air is clearly distinguishable from that of normal days without haze. Associated economic impacts include disruption to transport and tourism (Quah, 2002; Lee et al., 2016).

An air pollution event in Singapore can be considered as a random and exogenous shock in the quasi-experiment design for several reasons. First, local emissions are not the cause of the haze pollution experienced in Singapore. The local air pollution is trivial because of stringent industrial emission regulations in Singapore; most of the oil refineries and petrochemicals plants are located in Jurong Island, a reclaimed island west of the main island. This is reflected by the monthly average PSI value at around 40 in the absence of the haze pollution brought to Singapore by the wind. Second, the haze events in Singapore are exogenous because the air pollutants originate from Indonesia and depend on wind factors. Besides, as Figure 3 shows, the four haze episodes took place in different months in different years,

[3]Information on haze pollution is publicly available from the National Environmental Agency (NEA) of Singapore. To keep residents informed about the air quality, the agency regularly reports information on one-, two-, and three-hour measurements through radio, television, internet, mobile applications and other media. NEA also provides five different PSI descriptors to indicate the levels of pollution risks based on the PSI measures. PSI readings above 100 are considered threatening to health. PSI values from 201 to 300 are considered as 'very unhealthy', and PSI values above 300 are considered 'hazardous'. The NEA and the Ministry of Health (MOH) provide general advisories to local residents, especially concerning sensitive groups such as children, the elderly, pregnant women, and people with respiratory illness, so they will reduce their exposure to the pollution outdoors.

which indicates that the haze shock is less likely to be seasonable and predictable. Since Singapore offers an ideal environment for clearly identifying the causal relationship between air pollution and economic outcomes, the Jun 2013 and Sep-Oct 2015 haze episodes are particularly suitable for research (Sheldon and Sankaran, 2017).

## 2.2 Online Review Platforms of the Hospitality Industry

Tourism has become one of the largest and fastest-growing economic sectors in the world. The number of international tourist arrivals grew from 0.89 billion in 2009 to 1.24 billion in 2015 [4], and their travel expenditure rose by around 50% for the same period. In Singapore, the tourism receipts increased by 10% in 2017, reaching $12.7 billion (Statistics Singapore, 2018).

Online review websites and travel communities have become the most influential information source for travelers (Vermeulen and Seegers, 2009; Liu and Park, 2015). As reported by Blanke and Chiesa (2013), around 87% of international travelers have used the Internet for trip planning, and 43% have read the online travel reviews. The reviews enable tourists to share their experiences of places and products as well as to communicate with other travelers and with industry managers. In order to guarantee authenticity, the online process restricts reviews and comments to real travelers. Online reviews provide comprehensive information about consumer satisfaction with various attributes, such as the room facilities[5], the value for money[6], the location[7], sleep quality, cleanliness of the room, and service quality[8].

The user-generated contents are an electronic form of traditional word-of-mouth (E-WOM) marketing, which has a signicant impact on consumer buying decisions and willingness to pay (Chevalier and Mayzlin, 2006; Vermeulen and Seegers, 2009; Mudambi and Schuff, 2010). Online reviews that can reach large numbers of potential consumers have substantial E-WOM impact, and can therefore influence business outcomes for hotels. (Ye et al., 2011) find that a 10% increase in traveler review ratings can bring 5% or more additional reservations to hotels. Our paper argues that declining scores in online reviews touch a nerve of hotel managers, gain the attention of their teams, and generate incentives for hotels to improve services and efficiency.

[4]Data source: https://data.worldbank.org/indicator/ST.INT.ARVL.

[5]Category *room* refers to: amenities in the room/bathroom; size and layout of the room; welcoming extras.

[6]Category *value* refers to: room price; food and beverage price; and other prices.

[7]Category *location* refers to: Close to attractions; close to city centre; close to the airport/railway station; and accessibility.

[8]Category *service* refers to: Friendliness of the staff; language skills of the staff; efficiency of the staff in solving problems.

# 3 Data and Descriptive Statistics

The data is collected from multiple sources and can be grouped into two broad categories: hotel online reviews, and measures of ambient conditions. Table 1 presents a summary description of our data set, with online review data at the individual level reported in Panel A, and ambient conditions on a monthly basis reported in Panel B. Refer to Appendix A for detailed definitions of all variables used in the analysis.

The research context of the study concerns Singapore, an island country in Southeast Asia, and Hong Kong, a special administrative region of China in Eastern Asia. Singapore and Hong Kong share similarities in geological, economic, and cultural aspects. Table B2 in the Appendix compares Hong Kong and Singapore with known quantitative statistics. Both are Southeast Asian islands with a similar population size and population density. Hong Kong and Singapore are regional hubs for transport by air and sea, as well as being regional financial centers. Both are advanced economies with over 40,000 GDP per capita (PPP) in US dollars. Historically, Hong Kong and Singapore were colonies of the United Kingdom; and the economies in both regions started to rise rapidly in the 1970s to 1980s. The similarity between Singapore and Hong Kong relieves the possible treatment bias in the difference-in-differences estimations in the following sections.

## 3.1 Online Hotel Reviews

With the growing importance of online reviews, online platforms that allow travelers to share their experiences have become the leading source of information in tourism and hospitality. We developed crawlers using the Python language to auto-parse the web pages and extract the review data of all hotels in Singapore and Hong Kong between June 2012 and December 2016 from three widely used platforms: *TripAdvisor.com , Agoda.com, and Expedia.com*[9].

As Table 1 shows, the data contains 621,251 reviews from 413 hotels[10] and 32 hostels in Singapore, and 562,046 reviews from 533 hotels and 132 hostels in Hong Kong. It is notable that the hotels that stated operation after 2013 were excluded to avoid overestimation in the following analyses. We present a summary of hotels breakdown by star rating in Table B2 of Appendix B. The review scores in *TripAdvisor.com* and *Expedia.com* are on a 0-to-5 rating scale, while the review scores in *Agoda.com* are on a 0-to-10 rating scale. For the purpose

[9]We also collect online reviews from *Booking.com* and *Ctrip.com*, both of which are popular hotel-reservation platforms for travelers. However, the online reviews from *Booking.com* and *Ctrip.com* cover only a relatively short period from 2015 to 2017, during which Singapore was unaffected by severe haze. Therefore, we exclude the online reviews from *Booking.com* and *Ctrip.com*.

[10]Singapore Tourism Board reports that there are 413 licensed hotels as of December 2016, and our data includes online reviews from another 32 hostels where travellers can make reservations through the online platforms. See https://www.stb.gov.sg/industries/hotels for more details.

of easy interpretation and consistency, we re-scale the review score in *TripAdvisor.com* and *Expedia.com* on a scale from 0 to 10, with a higher score corresponding to a higher evaluation on the service quality. The average online review scores in Singapore and Hong Kong are quite close, but the standard deviation is slightly higher in Singapore.

[**Table 1 inserted here**]

Figures 1 and 2 display the geographic distributions of hotels in Singapore and Hong Kong, respectively. Luxury hotels (five-star hotels) are located mainly in the central business districts in both regions. We also plot the quantile distribution by hotel daily room prices at the neighborhood (sector) level. The demographic characteristics, including country of origin and traveller type, of travellers in our sample are listed in Table B3 of Appendix B. Targeted consumers in terms of their country of origin and types are very similar between Singapore and Hong Kong.

[**Figures 1 and 2 inserted here**]

The review data collected from the websites of *TripAdvisor.com, Agoda.com, and Expedia.com* contains a rich set of information including a traveller's review score, review date, stayed month, account name, guest type (such as business, couple, family, friends, group, solo traveller, and other), and guest country of origin (there are 216 countries in the sample), as well as the contents of each review. Among 621,251 reviews on hotels of Singapore, 188,660 (30.37%) are from *TripAdvisor.com* , 374,361 (60.26%) come from *Agoda.com*, and 58,230 (9.37%) are provided by *Expedia.com.* The distribution of reviews on hotels in Hong Kong is 125,765 (22.38%), 373,315 (66.42%), and 62,966 (11.20%) from *TripAdvisor.com , Agoda.com, and Expedia.com*, respectively.

Moreover, the data collected from *TripAdvisor.com* and *Expedia.com* provides additional information on whether hotel managers respond to guests reviews. Specifically, the data includes the response content and response date. For example, among 246,890 reviews in *TripAdvisor.com* and *Expedia.com* in Singapore, 125,890 (50.99%) are responded by the hotel managers. In addition, *Expedia.com* categorizes each review into either a positive or a negative comment. Of 58,230 reviews in *Expedia.com*, 15,162 (26.04%) are include a negative comment.

It is worth noting that *TripAdvisor.com* also presents the subcategory review scores of six different attributes related to a stay: *cleanliness, service, location, room, value* and *sleep quality*. We define two groups of subcategory review scores based on whether the service in a subcategory area can be improved by efforts made through the hotels' daily operations. In particular, *cleanliness*, *service*, and *value* are assigned to the improvable group, while *location* and *room* are assigned to the non-improvable group. Sleep quality belongs to neither improvable group nor non-improvable group because it can be subjective, objective or both.

Figure B1 in Appendix B plots the monthly frequency of online reviews for hotels in

Singapore and Hong Kong from June 2012 to December 2016. Given that the monthly count of reviews exhibits a small variance along the sample period, the sample measurement error and sample selection bias are less likely to be concerns in the following empirical analysis.

## 3.2 Air Pollution and Weather Measures

### 3.2.1 Air Quality Data in Singapore

For the air quality information in Singapore, we collect 24-hour PSI readings from the National Environment Agency (NEA)[11] for the period between June 1, 2012 and December 31, 2016. The readings, which range from 0 to 500, are reported by the NEA through mass media, such as television, radio, the Internet and mobile applications, to inform residents about air quality. The 24-hour PSI value provides an hourly indication of the air quality by averaging the data collected over the past 24 hours[12]. The 24-hour PSI reading is a composite measure of the concentrations of multiple pollutants, which includes particulate matter ($PM_{10}$), fine particulate matter ($PM_{2.5}$), sulfur dioxide ($SO_2$), nitrogen dioxide ($NO_2$), Ozone ($O_3$), and carbon monoxide ($CO$). We use a linear interpolation method to address the missing observations in the hourly PSI readings, and calculate the monthly average and monthly maximum of PSI readings.

### 3.2.2 Air Quality Data in Hong Kong

For pollution information in Hong Kong, we turn to the Air Quality Index (AQI) provided by the Environmental Protection Department (EPD) of Hong Kong[13]. The AQI contains the raw daily records of $PM_{10}$, $PM_{2.5}$, $SO_2$, $NO_2$, $O_3$, and $CO$ from 13 ambient air quality monitors throughout Hong Kong. Since PSI measures are not readily available in Hong Kong, we construct the PSI measure following the method used by NEA Singapore[14]. More specifically, we compute a sub-index value for each pollutant based on the ambient air concentration of the pollutant, and take the highest sub-index value as the PSI value. Compared to AQI, PSI is determined by the pollutant with the most significant concentration. For analysis use, we calculate the monthly average and monthly maximum of PSI readings.

[11] Data Source: https://www.haze.gov.sg/

[12] For the period prior to August 24, 2012, the 24-hour PSI readings were recorded only once per day, whereas a more regular reporting of three 24-hour PSI readings are available per day for the period from August 24, 2012 to June 20, 2013.

[13] Date source: http://www.epd.gov.hk/epd/english/environmentinhk/air/air_quality/air_quality.html

[14] The methodology of PSI in Singapore: https://www.haze.gov.sg/docs/default-source/faq/computation-of-the-pollutant-standards-index-(psi).pdf

### 3.2.3 Weather Data in Singapore and Hong Kong

In relation to travellers' experiences, weather conditions could confound the effects of air pollution. To avoid the possible contamination, we collect other weather information from a weather company[15], as well as from the official websites of NEA Singapore and EPD Kong Kong.

The weather company provides hourly information on visibility and weather status for the sample period in Singapore and Hong Kong. Specifically, visibility is based on the distance at which an object or light can be detected, and the larger number indicates a clearer visibility. We calculate the monthly average of visibility for both regions. The data from the weather company also includes 18 weather keywords to indicate the weather status of each hour. Based on these keywords, we create the "Days of Haze (DoH)" variable, which aggregates the number of days per month that contain the keywords *"light haze," "haze," or "heavy haze"*. DoH is considered as an alternative measure of air quality in our study. The official websites of NEA Singapore and EPD Hong Kong contains historical information on temperature, total rainfall, and wind speed.

### 3.2.4 Summary Statistics of Weather Data and Air Quality Data

Figure 3 and Figure 4 plot the monthly trends of mean PSI (dashed line) and maximum PSI (dotted line), as well as the monthly average online review score from June 2012 to December 2016 in Singapore and Hong Kong, respectively. Based on the severity and duration of 24-hour PSI readings, we identify two severe and two mild haze shocks in Singapore. The dark shaded areas and large spikes highlight two strong haze shocks in Jun 2013 and Sep-Oct 2015, while the light shaded areas represent two mild haze episodes in Oct 2014 and Aug 2016. The width of shaded areas indicates the duration of air pollution events. In contrast, the mean PSI and maximum PSI in Hong Kong are relatively stable and low during the sample period, suggesting that Hong Kong is free of haze shocks. Moreover, to precisely examine the dynamics of the review score before, during, and after the haze shocks, we divide the sample period into four periods: Jun 2012 to May 2013 (period 1, the pre-shock period of the Jun 2013 haze), Jul 2013 to Aug 2014 (period 2, the post-shock period of the Jun 2013 haze), Dec 2014 to Aug 2015 (period 3, the pre-shock period of the Sep-Oct 2015 haze), and Nov 2015 to Dec 2016 (period 4, the post-shock period of the Sep-Oct 2015 haze).

As shown in Panel B of Table 1, both the monthly average and monthly maximum PSI readings in Singapore are around 1.5 times large as that in Hong Kong. The peak of the max PSI in Singapore reached 297, while the highest monthly max PSI Hong Kong just touched 87. The larger maximum value in association with the greater volatility in measures of air

[15]Data Source: https://www.wunderground.com/

pollution in Singapore compared to Hong Kong can be explained by the phenomenon of haze shocks. As Figures 3 and 4 show, the scores of online reviews in Singapore drop significantly during haze shocks, especially during the two severe haze episodes, while the review scores of hotels in Hong Kong remain stable all the time. Figure 3 provides unconditional evidence of a negative relationship between PSI and review score. More interestingly, we find that the review score reverts to, and even exceeds, the magnitude before the haze episode. In line with the PSI measure, another measure of the air quality, days of haze (DOH), is also significantly larger in Singapore than in Hong Kong.

For other weather data as shown in Panel B of Table 1, the temperature is 3.2 centigrade higher in Singapore than in Hong Kong. Both regions labeled with ”hot” as their average temperatures are higher than 24 centigrade. Hong Kong experienced more rainfall and wind on average than Singapore. The visibility measure in Singapore is lower than in Hong Kong because of the occasionally occurred haze shocks. However, skies in both regions are usually clear as their visibility measures are larger than 9 km.

[**Figure 3 inserted here**]

[**Figure 4 inserted here**]

# 4 Conceptual Framework

We construct a simple conceptual framework to illustrate incentives for hoteliers to improve their service quality ex-post a detrimental haze shock. We consider the reputation (average review score) of a hotel to be subject to the exogenous weather condition, and to the effort expended by the hotel towards service quality. The reputation function is denoted as $L = L(q, e)$, with $q$ corresponding to the exogenous ambient pollution (i.e., haze shock) and $e$ corresponding to the effort input. For simplicity, we consider $e$ as the cost for serving one guest and hotels are homogeneous. One unit of $L(q, e)$ brings $p$ income for the hotel. Reputation is an increasing and concave function of effort; that is $L_e > 0$ and $L_{ee} < 0$. We also assume that the review score decreases with the ambient pollution, which leads to the decreased reputation of the hotel: $L_q < 0$. The hotel's goal is to maximize its utility through benefiting from the reputation $L$ and paying a cost on the effort $e$:

$$max\ U(L(q, e), e),\ subject\ to\ p < e$$

Assuming an interior solution to the maximization function, we can rearrange the total derivative of $L = L(q, e)$ to present the following equation for the partial effect of ambient pollution on reputation:

$$\frac{\partial L}{\partial q} = \frac{\mathrm{d}L}{\mathrm{d}q} + \frac{\partial L}{\partial e} \times \frac{\partial e}{\partial q}$$

This expression is useful in illustrating that the partial derivative of reputation with respect to pollution is equal to the sum of the total derivative and the product of the partial derivative of reputation with respect to effort (assumed to have a positive sign) and the partial derivative of effort with respect to pollution (assumed to have a positive sign). Following the literature of environmental health (Grossman, 1972; Graff Zivin and Neidell, 2013; Deschênes et al., 2017), we can interpret the effort $e$ as avoidance behavior by the hotel, which tries to lessen the negative impact of pollution on its reputation by providing guests with better service.

When severe ambient pollution $\bar{q}$ such as a haze episode appears, the hotels face a trade-off between two choices: (1) benefiting from a lower reputation, $L = L(\bar{q}, e)$, but paying an unchanged cost $e$; (2) maintaining the reputation at its original level by paying a higher cost $\bar{e}$. Intuitively, to avoid any possible customer churn, hotels would chose to save their reputations damaged by ambient pollution by expending greater effort on the service quality if the profit loss is greater than the cost of the effort required to maintain their original level of reputation.

# 5 Reduced Form Evidence

Following a threefold empirical strategy, we study the impact of a random exogenous weather shock on online hotel reviews, which in turn affects the operational efficiency of hotels. First, we examine whether and how exogenous variations in air quality affect online review scores by using an event study method for hotels in Singapore. We also compare the trends of online review scores for hotels in Singapore and Hong Kong in a difference-in-differences analysis. Moreover, we study the dynamic responses of review scores before, during, and after the haze shock. Second, to understand the underlying mechanisms through which haze pollution affects travelers' lodging experience, we study the heterogeneity in the response across subcategory review scores. As stated in Section 3.1, we classify the attributes of a review score in TripAdvisor into an improvable category (such as *cleanliness*, *service*, and *value*) and a non-improvable category (such as *location* and *room*), which are the treatment and control groups in the difference-in-differences design, respectively. We further conduct a triple differences analysis, which compares the improvable category to the non-improvable category between hotels in Singapore (treatment region) and Hong Kong (control region) with and without haze shocks. Third, we examine how managers' responses to online reviews impact online review scores to determine why review scores rise after the decline during the haze episodes.

We use several measures to identify haze episodes from Jun 2012 to Dec 2016. First, the monthly average ($PSI^{mean}$) and monthly maximum ($PSI^{max}$) 24-hour PSI readings are the most direct way of measuring the haze intensity in the study period. We also create two binary variables to identify the haze shocks, $Shock^a$ and $Shock^b$. As shown in Figure 3, there are four haze shocks (in shaded areas) during the period, as identified by $Shock^a$. $Shock^b$ represents two severe shocks in Jun 2013 and Sep-Oct 2015. More specifically, the haze shock in Jun 2013 was relatively short-lived (one-week long), while the haze shock in late 2015 lasted for 7 weeks. In addition, we use $DoH$ to measure the number of days per month with haze status; and we classify the monthly average $PSI^{max}$ into three categories: 0-60, 61 to 120, and above 120, to create a categorical variable $PSI\ category$ to identify three levels of haze.

## 5.1 The Causal Relationship between Air Pollution and Online Review Scores

First, we employ a weather-shock approach to investigate the reduced-form relationships between various haze measurements and online review scores using online review data of Singapore hotels. The reduced-form weather-shock approach makes few identification assumptions and allows strong causative interpretation (Dell et al., 2014). A necessary condition for the event study is the exogeneity of the weather shock. Since the haze episodes in Singapore are random and exogenous shocks, they suit the study particularly well.

We analyze the responses in online review scores to the changes of air quality using the following econometric model:

$$Score_{i,j,k,t} = \alpha + \beta \cdot Haze_t + \gamma \cdot X_t + \mu_g + \delta_o + \zeta_j + \eta_k + \theta_{year} + \theta_{month} + \epsilon_{i,j,k,t} \qquad (1)$$

where $i$, $j$, $k$, $t$, $g$, and $o$ index reviewers, hotels, websites, stayed year-month, guest type, and guest origin country, respectively. The dependent variable $Score_{i,j,k,t}$ is the online review score of reviewer $i$ rates for his/her stay in year-month $t$ at hotel $j$ on website $k$. It should be noted that $t$ is the year-month in which the online reviewers stayed at the hotel, not the time they posted their review. $Haze_t$ represents the various air quality measures ($Shock^a$, $Shock^b$, $PSI^{mean}$, $PSI^{max}$, $DoH$, $category\ PSI$) in year-month $t$. To control for weather conditions that could possibly affect guests' lodging experiences, we add a vector of other time-varying observations, $X_t$, which includes the logarithmic terms of temperature, rainfall, wind speed, and visibility in year-month $t$.

In addition, we control for a rich set of fixed effects, which isolates our estimations on the haze impact from other unobservable contaminations. $\mu$ and $\delta$ stand for the guest type fixed effect and the guest origin country fixed effect, respectively, which capture factors that possibly impact online review scores at individual level. $\zeta$ is hotel fixed effect, which absorbs the fixed spatial unobservable characteristics across hotels. $\eta$ is a website fixed effect that eliminates the differences of construction of the review score across the three websites. $\theta_{year}$ and $\theta_{month}$ represent the year fixed effect and month fixed effect, respectively, which absorbs the time variations of online review scores and neutralizes the seasonality. The reason we control for year fixed effect and month fixed effects rather than year-month fixed effect is that including year-month fixed effect would absorb any month-to-month variation in economic and weather conditions in Singapore, which would therefore eliminate our key variable $Haze_t$. Given that online reviewers may be influenced by the existing reviews of the hotel they are rating, review scores for a hotel may be correlated. Thus, all standard errors are robust and clustered at the hotel level, which allows an arbitrary variance-covariance matrix to capture the potential serial correlations in the residual error terms.

Table 2 presents the regression results of estimating Equation (1) using online review data of hotels in Singapore from Jun 2012 to Dec 2016. The results provide clear evidence of a causal relationship between air pollution and online review scores. As shown in Columns 1 and 2, the average online review score is around 0.268 points lower during four haze episodes, and the magnitude of the drop of review scores is greater at -0.351 during the two heavy haze episodes. Columns 3 and 4 show that as the PSI readings double, the review scores decrease by 0.264 to 0.278, on average. During a severe haze shock, when the 24-hour PSI readings increase six times from 50 to 300 and a linear relationship is assumed between the PSI readings and online review scores, the estimated drop of online review scores can be as large as 1.6 on a 0-to-10 scale. Column 5 indicates that one additional hazy day decreases the monthly average online review score by 0.031. Following Chang et al. (2016), we model the monthly PSI reading with a series of indicator variables to allow for a nonlinear effect of PSI. As shown in Column 6, we continue to find consistent evidence that online reviews respond negatively to PSI. We find that on average PSI levels from 61 to 120 lower the review scores by 0.039 points, and that when PSI levels jump over 120, the negative effects on review scores are much greater to a level of -0.382 points. In addition, we conduct the same analysis by focusing on the first severe haze shock in Jun 2013 and restricting the sample period between Jun 2012 and Aug 2014. Analyses on a short period reduce the concern that our results are contaminated by other unobserved hotel-level shocks. The results are presented in Appendix Table B4. The estimated coefficients are statistically significant with larger magnitudes.

**[Table 2 inserted here]**

We then study the ex-ante versus ex-post responses of online review scores to haze shocks to determine whether review scores return to the previous level after a haze shock using the following specification:

$$Score_{i,j,k,t} = \alpha + \beta \cdot Post + \gamma \cdot X_t + \mu_g + \delta_o + \zeta_j + \eta_k + \theta_{year} + \theta_{month} + \epsilon_{i,j,k,t} \quad (2)$$

where *Post* is a binary variable equal to 1 for the period after the haze shock. The fixed effects are the same as those in Equation (1). As stated previously, we divide the sample period into four periods and examine the changes of review scores after the two severe haze shocks (Jun 2013 and Sep-Oct 2015), compared to the period before the shocks.

Table 3 provides the results of estimating Equation (2) under different combinations of sample periods (see Figure 3). The coefficients on *Post* in Columns 1 and 3 capture the differences between the online review scores before and after the two severe haze shocks. Columns 2 and 4 conduct additional robustness checks by comparing the review scores to alternative pre- or post-shock periods. The coefficient in Column 1 indicates that the average online review score increases by 0.224 points for the post-shock period 2 (Jul 2013 to Aug 2014) after the June 2013 haze shock, compared to the average online review score in the pre-shock period 1 (Jun 2012 to May 2013). Column 3 presents the estimation for the Sep-Oct 2015 haze shock and shows that the average online review score in the post-shock period 4 (Nov 2015 to Dec 2016) is 0.216 points higher than that in the pre-shock period 3 (Dec 2014 to Aug 2015).

**[Table 3 inserted here]**

It is worth noting that period 2 is the post-shock period of the Jun 2013 haze shock; and period 3, the following period, is the pre-shock period of the Sep-Oct 2015 haze episode. In Column 2, we compare period 3 to period 1, and the coefficient on *Post* is positive but statistically insignificant, suggesting that the increment in online review scores after the June 2013 haze shock may not be persistently large. Figure 3 shows that a mild haze shock took place in 2014, which might have affected the online review scores in the pre-shock period of the Sept-Oct 2015 haze. Therefore, in Column 4 of Table 3, we compare period 4 to period 1, which is the pre-shock period free of any haze effect, as a robustness check to provide a more precise comparison between the ex-ante and ex-post responses. The coefficient on *Post* is positive and statistically significant at 0.247, and it is greater than the coefficient in Column 3.

Although the weather-shock approach allows for a strong causal interpretation of the relationship between air pollution and online review scores, we do not observe a counterfactual status as all hotels in Singapore have been exposed to the haze episodes. To measure the causal effects of air pollution on online review scores, it is essential to simultaneously observe reviews on hotels affected by haze episodes and reviews on hotels unaffected by haze episodes. This drives us to estimate the counterfactual state by utilizing online review data of all the hotels in Hong Kong as a control group and conducting a difference-in-differences analysis. This approach requires three assumptions: first, the random assignment of the treatment and control groups; second, hotels in Singapore (treatment group) and Hong Kong (control group) are comparable; third, a parallel trend in online review scores between the treatment group and the control group before the haze shock.

The first assumption is well satisfied thanks to the exogeneity of the haze shock in Singapore. For the second assumption, Panel B of Table 1 and Panel B of Appendix Table B2 show that Singapore and Hong Kong are similar in terms of climatic conditions, economic development, and cultural factors. Moreover, Panel A of Appendix Table B2 indicates that hotels in Singapore and Hong Kong are comparable in star rating; and Appendix Table B3 illustrates that the guests' characteristics, including country of origin and guest types, in both regions are similar[16]. In addition, even hotels in naturally different regions have the same goal, that is to provide the best service and attract as many customers as possible. Therefore, we are confident that hotels in Singapore and Hong Kong are comparable. The third assumption is also satisfied, and further details on this assumption are discussed in Table 5.

Notably, we conduct the event study only on the first severe haze shock, which took place in June 2013, in our difference-in-differences analysis for two reasons. First, the test on the first severe haze shock is cleaner because it is immune from the expectation issue, as well as the previous haze effect[17]. Second, focusing on a relatively short period mitigates the possibility of our estimation being contaminated by other events and weather shocks, e.g., the Singapore general selection.

Our difference-in-differences specifications are as follows:

$$Score_{i,j,k,t} = \alpha + \beta \cdot Haze_t + \phi \cdot Treatment_c \cdot Haze_t + \gamma \cdot X_t + \mu_g + \delta_o + \zeta_j + \eta_k + \theta_t + \epsilon_{i,j,k,t} \quad (3)$$

$$\begin{aligned} Score_{i,j,k,t} =& \alpha + \beta_{pre} \cdot Treatment_c \cdot 1_{pre} + \beta_{post} \cdot Treatment_c \cdot 1_{post} + \gamma \cdot X_t + \mu_g + \delta_o \\ &+ \zeta_j + \eta_k + \theta_t + \epsilon_{i,j,k,t} \end{aligned} \quad (4)$$

where Equation (3) studies the response of the online review scores during the haze shocks; and Equation (4) compares the changes of the online review scores before and after the haze shocks, excluding the period with haze shocks. The sample period for estimating Equations (3) and (4) is from Jun 2012 to Aug 2014 (that is periods 1 and 2 as shown in Figure 3). More specifically, $Haze_t$ in Equation (3) represents different haze measures in year-month $t$, and $Treatment_c$ is a binary variable equal to 1 for hotels in Singapore, and is equal to 0 for hotels in Hong Kong. $\phi$ captures the causal effects of air pollution to online review scores. It is worth noting that we control for year-month fixed effect $\theta_t$ in Equations (3) and (4) instead of the year fixed effect and month fixed effect included in Equations (1) and (2), because monthly weather conditions are different in Singapore and Hong Kong[18]. Other

[16] 19 of the top 20 country of origin for the hotel guests in Singapore and Hong Kong are the same. The compositions of the guest types in Singapore and Hong are quite similar.

[17] Tests on the September-October 2015 haze would be less precise as they might suffer from contaminations from the June 2013 haze shock.

[18] Year-month fixed effect is supposed to absorb more unobserved variation across time than year fixed

fixed effects are the same as those in Equation (1).

$1_{pre}$ in Equation (4) is a binary variable equal to 1 for the six months (i.e., Dec 2012-May 2013) before the June 2013 haze shock, and $1_{post}$ is a binary variable equal to 1 for twelve months after the haze shock. $\beta_{post}$ captures the average responses of online review scores for hotels in Singapore (compared to the benchmark period, which refers to the first six month, Jun 2012 to Nov 2012, of the pre-shock period), relative to the post-shock changes on online review scores of hotels in Hong Kong. $\beta_{pre}$ measures the differences of online hotel review scores between the treatment group and the control group during the six pre-shock months (compared to the benchmark period). For a robustness check, we also use two alternative $1_{pre}$, Sep 2012-May 2013 and Feb 2013-May 2013. Validity of the difference-in-differences design assumes a parallel trend in online review scores of hotels in Singapore and Hong Kong before the shock, and requires $\beta_{pre}$ to be statistically and economically indistinguishable from 0.

Table 4 provides our main estimates of interest – the results of the difference-in-differences Equation (3), which compare the responses of online review scores to air pollution between hotels in Singapore and Hong Kong. Columns 1 to 4 use various haze measurements, and the haze effects are captured by the interaction term $Treatment_c * Haze_t$. In all specifications, the interaction coefficient $\beta$ is consistently estimated to be significantly negative. Column 1 suggests that online reviews of hotels in Singapore are 0.408 points lower on a 0-to-10 scale during the haze episodes, compared to online reviews of hotels in Hong Kong, which were not affected by air pollution shocks. Columns 2 and 3 use a logarithm of monthly maximum PSI and mean PSI to measure the intensity of air pollutants, and show that the online review scores of hotels in Singapore decrease by 0.149 to 0.266 points more relative to Hong Kong if PSI values double. In addition, as shown in Column 4, each additional hazy day decreases the review scores of hotels in Singapore by 0.057 points, on average.

[**Table 4 inserted here**]

Table 5 reports the results of the changes of online review scores by applying Equation (4). The coefficients on $Treatment_c$*$Pre$ show the differences in online review scores between hotels in Singapore and Hong Kong in the pre-shock period compared to the benchmark period in the sample period. More specifically, Columns 1 to 3 present results using a different pre-trend duration and a different benchmark period; and the coefficients of the pre-treatment period variable $Treatment_c$*$Pre$ are economically small and statistically insignificant, suggesting that there are no differences in the online review scores change pattern between hotels in Singapore and Hong Kong before the haze shock. This verifies the third assumption for the DID design as stated. The coefficients on $Treatment_c$*$Post$ capture the online review scores responses after the haze shocks compared to the benchmark period.

effect and month fixed effect.

Overall, the ex-post responses on online review scores are both statistically and economically significant, and online review scores for hotels in Singapore rise by 0.256 to 0.279 points on average in the post-shock periods.

[**Table 5 inserted here**]

To gauge the dynamic effect of the air pollution shock on the online review scores, we estimate a distributed lag model following Agarwal et al. (2007) and Agarwal and Qian (2014):

$$Score_{i,j,k,t} = \alpha + \sum_{s=-6}^{12} \beta_s \cdot Treatment_c \cdot 1_{month\ s} + \gamma \cdot X_t + \mu_g + \delta_o + \zeta_j + \eta_k + \theta_t + \epsilon_{i,j,k,t} \quad (5)$$

where coefficients $\beta_{-6}$,..., $\beta_{-1}$ stand for the difference of response in online review scores between hotels in Singapore and hotels in Hong Kong in each of the six pre-shock months. Similarly, the marginal coefficients $\beta_1$,..., $\beta_{12}$ capture the additional marginal effects one month,..., twelve months after the haze shock, respectively.

By estimating Equation (5), we can derive the dynamic responses of online review scores pattern during the 12-month post-shock period beginning from six months before the Jun 2013 haze shock. Figure 5 graphs the entire paths of dynamic coefficients $\beta_s$ (indicated by the solid line), where $s$=-6, -5,..., 11, 12. The dotted lines depict the corresponding 95 confidence intervals. As previously noted, the patterns of online review scores between hotels in Singapore and hotels in Hong Kong during the six-months pre-shock period are insignificant, both statistically and economically. Online review scores of hotels in Singapore drop substantially during the haze shock (in Jun 2013), but the drop is temporary; as Figure 5 shows, the average review score rises immediately after the haze shock by 0.42 points by the end of the second month after the Jun 2013 shock compared to the average score six months before the shock[19]. It is important to note that the sharp rise in the average review score is short-lived and observed only in the first two months following the haze shock. Consistent with the results in Table 3, the coefficients start to decrease and remain around 0.15 six months after the haze shock.

[**Figure 5 inserted here**]

We also perform the estimations of Equation (5) separately for the six subcategory review score and plot the results in Figure 6. Although almost all the rating categories have experienced declines during the haze episodes, only *cleanliness*, *service*, and *value* show significant upward trends after the haze shock, suggesting that significant improvements have

[19]We conjecture that the reason the review score did not rise sharply in the first month ex post the haze shock is twofold: first, the guests did not write the review during the stay; second, the manager should first see the review and then supervise the staff to improve service. Both are reasons for the delay in the rise in review scores after the haze shock.

been made by hotels in those areas in order to boost hotels reputation. Figure 6 also serves as criteria for us to group the subcategory review scores into improvable and non-improvable sectors as aforementioned.

[**Figure 6 inserted here**]

## 5.2 The Reputation-Performance Relationship: Why and How do Online Review Scores Change?

We have demonstrated that during a haze shock, review scores drop sharply, and then quickly rise again following the period of haze. This raises the questions of how and why the review scores change, and whether travelers' reactions are affected directly by the environmental shock, by their hotel experience, by their mood, or by a combination of these. To answer this question, we look at subcategory online review scores in this section. Evans et al. (1987) show that air pollution has negative mood effects. We hypothesize that unhealthy air quality, mediated by mood, may lead to a collective changes in the level of customer satisfaction, resulting in lower review scores.

Before considering Equations (6) and (7), we first use Equations (1) and (2) to examine guests' responses in each subcategory of the online reviews during and following the first severe haze shock. Table 6 contains the results, where Panel A and Panel B correspond to the responses during and following the shock, respectively. In panel A, we find that in the categories of *sleep*, *location*, and *value*, guests respond negatively to the haze in the period of the shock, but find no responses in the categories of *cleanliness*, *service* and *room*. This is consistent with the results of the dynamic analysis shown in Figure 6. At the same time, the unchanged ratings of *service* and *cleanliness* would suggest that the level of service quality did not drop. These results indicate that the main contributor to the increase in negative responses related to the haze shock could be the mood of the guests rather than service quality. For instance, as shown in Panel A, the rating on *location* decreases because the utility to guests of a hotel stay is greatly reduced if they can barely see anything from their window in the famous Marina Bay Sand hotel in Singapore. However, the hotels cannot do anything to improve the guests' satisfaction on *location*, as *location* measured the objective aspects such as proximity to attractions and transportation accessibility.

Moreover, as shown in Panel B, ratings of *cleanliness*, *service*, and *value* increase significantly in the post-shock period, while ratings of *location*, *sleep quality*, and *room* remain unchanged. We also estimate Equation (4) using the six subcategory review scores, separately, and report the results in Appendix Table B5. The results are similar to that in Panel B of Table 6. The results in Figure 6 and Table 6 justify the validity to classify the subcategory review scores into improvable and non-improvable groups. As shown in Figure

6 and Panel B of Table 6, *cleanliness* and *service*, which are related to service quality, and *value*, which measures guests' subjective value perception of a stay, are improved after the shock. In addition, *location* and *room* are objective aspects of the hotel services and remain unchanged after the haze shock, compared to their scores before the shock. *Sleep quality* belongs to neither improvable group nor non-improvable group because it can be subjective, objective or both.

**[Table 6 inserted here]**

The difference-in-differences method in the previous section provides the comparison to hotels in another region that were not exposed to air pollution in order to identify the causal relationship between air pollution and online review scores. In this section, our empirical strategy is twofold to understand the underlying mechanisms through which air pollution affects travellers. We first employ a traditional difference-in-differences approach that compares the changes in subcategory online reviews scores before and after haze shocks of hotels in Singapore; and then further examines the changes in review scores of the improvable category in Singapore (the treatment region) relative to changes in review scores of the improvable category in Hong Kong (the control region) using a triple differences approach (Gruber, 1994; Hamermesh and Trejo, 2000).

We estimate regression equations in the following forms:

$$\begin{aligned} Score_{i,j,k,p,t} = &\alpha + \beta_{pre} \cdot Treatment_p \cdot 1_{pre} + \beta_{post} \cdot Treatment_p \cdot 1_{post} + \gamma \cdot X_t + \mu_g + \delta_o + \zeta_j \\ &+ \eta_k + \nu_p + \theta_t + \epsilon_{i,j,k,p,t} \end{aligned} \tag{6}$$

$$\begin{aligned} Score_{i,j,k,p,t} = &\alpha + \beta_1 \cdot Treatment_c \cdot Treatment_p \cdot 1_{pre} + \beta_2 \cdot Treatment_c \cdot Treatment_p \cdot 1_{post} \\ &+ \beta_3 \cdot Treatment_c \cdot 1_{pre} + \beta_4 \cdot Treatment_c \cdot 1_{post} + \beta_5 \cdot Treatment_p \cdot 1_{pre} \\ &+ \beta_6 \cdot Treatment_p \cdot 1_{post} + \gamma \cdot X_t + \mu_g + \delta_o + \zeta_j + \eta_k + \nu_p + \theta_t + \epsilon_{i,j,k,p,t} \end{aligned} \tag{7}$$

where $p$ indexes the subcategory of online review scores. $Treatment_p$ is a binary variable equal to 1 for improvable category review scores, 0 for non-improvable ones. Equation (6) studies the difference in the responses of subcategory online review scores (e.g., improvable category and non-improvable category) to the air pollution for hotels in Singapore using the difference-in-differences approach. Equation (7) utilizes hotel reviews in both Singapore and Hong Kong and compares the haze effects to improvable and non-improvable categories using a triple differences method. Additional subcategory fixed effects and year-month fixed effects are included in both specifications. Other fixed effects are the same as those in Equation (1). $\beta_{post}$ in Equation (6) and $\beta_2$ in Equation (7) are the coefficients of interest.

Table 7 presents the results with Panel A (Columns 1 to 3) corresponding to the estimation of Equation (6) and Panel B (Columns 4 to 6) corresponding to the estimation of Equation (7). Following the tests in Table 5, we conduct the estimations on different pre-shock periods and different benchmark periods for robustness. For the DID estimations on subcategory review scores in Singapore (Columns 1 to 3), we find a significant increase in the scores of improvable category (treatment group) in all time windows. The ex-post responses of the treatment group are both statistically and economically significant, corresponding to an increase of 0.251 to 0.276 points in the twelve-month period after the haze shock, compared to the scores of non-improvable category (control groups). Moreover, the coefficients on $Treatment_t$*$Pre$ are both economically small and statistically insignificant in the different pre-shock periods (e.g., -9 months, -6 months, and -3 months), suggesting that there is no difference in the score changing pattern between the improvable category and the non-improvable category before the haze episode. Since we control for year-month fixed effect in Equations (6) and (7), the monthly weather measures are omitted in Panel A. To gauge the sensitivity of our results to the exclusion of year-month fixed effect, we re-run the regressions of Equation (6) with the year fixed effect, month fixed effect and other weather conditions included instead. The results are consistent and the magnitudes of the interactions barely changed. The results are reported in Table B6 in Appendix B.

[**Table 7 inserted here**]

Panel B of Table 7 (Columns 4 to 6) gives the estimates of the triple differences approach. The coefficients of the triple interaction of $Post$ are estimated at 0.215 in all three specifications, suggesting a 0.215 point increase in the scores of improvable category in treatment region, compared to the change in the scores of improvable category in control region. This statistically significant DDD estimate provides some evidence that the hotels in Singapore enhanced their service quality ex- post the haze episode to save the reputation and avoid customer churn. Our estimate of $Treatment_c$*$Post$, the increase in online review scores of hotels in Singapore in the post-shock period, is around 0.165 points. The magnitude is smaller than the estimate using the traditional difference-in-differences approach in Table 5, which compares changes in online review scores between hotels in Singapore and Hong Kong. Moreover, in all three columns of coefficient estimates of the pre-shock period variable ($1_{Pre}$) interact with either treated region ($Treatment_c$) or treated subcategory ($Treatment_p$) are both economically small and statically insignificant, satisfying the assumption of common trend between the treatment and control groups. As Singapore and Hong Kong are subject to different weather conditions, the inclusion of year-month fixed effect does not render weather measures omitted. We find the coefficients of all the weather measures are statistically insignificant. To save space, we do not show the results of weather condition measures here.

### 5.3 Potential Mechanisms: Do Manager Responses Play a Role?

According to the marketing and management literature (Mizerski, 1982; Cheema and Papatla, 2010), hotel managers may be prompted by negative online reviews to improve their service quality in order to raise their hotel's online reputation. Managers' responses to online reviews have become an important part of customer relationship management (Gu and Ye, 2014). As suggested by the reciprocation theory (Jones, 1966), managers can show that they listen to and appreciate their customers by responding to positive online reviews. Moreover, according to the service recovery theory (Wallin Andreassen, 2000), managers' responses to negative online reviews can help the management team to address service issues and improve customer satisfaction (Xie et al., 2014).

Research indicates that managers' responses to online reviews impact business outcomes (Gu and Ye, 2014). In an analysis of the online reviews on *Ctrip.com*, a review and e-commerce website for travel goods in China, Gu and Ye (2014) find that consumer satisfaction increases when hotel managers respond to consumer complaints. In a study of the online reviews and manager responses on *TripAdvisor.com*, Xie et al. (2014) find that managers' responses to online reviews about the location of the hotel have a positive impact on the hotel's performance, whereas responses to reviews about the cleanliness of the hotel have a negative effect.

To understand whether managers' responses play a role in the ex-post changes of online review scores, we propose the following hypotheses:

**H1**. Reviewers who stayed in hotels during the haze episodes are more likely to leave negative comments.

**H2**. Managers are more likely to respond to reviews of lower scores.

**H3**. Managers are more likely to respond to reviews covering a haze-episode stay.

**H4**. Managers' responses positively influence the online review scores in the next period.

We use the following logit models to study the likelihood of reviewers leaving negative comments during haze episodes and the likelihood of hotel managers responding to online reviews covering a haze-episode stay in Singapore:

$$logit(Negative.Comment_{i,j,t}) = \alpha + \beta \cdot Haze_t + \gamma \cdot X_t + \mu_g + \delta_o + \zeta_j + \theta_{year} + \theta_{month} + \epsilon_{i,j,t} \quad (8)$$

$$\begin{aligned} logit(Response_{i,j,k,t}) =& \alpha + \beta \cdot Haze_t + \phi \cdot Score_{i,j,k,t} + \gamma \cdot X_t + \upsilon \cdot Sentence_{i,j,k,t} + \\ & \mu_g + \delta_o + \eta_k + \zeta_j + \theta_{year} + \theta_{month} + \epsilon_{i,j,k,t} \end{aligned} \quad (9)$$

where the dependent variable $Negative.Comment_{i,j,t}$ in Equation (8) is a binary variable equal to 1 if a traveller leaves a negative comment for his/her stay in the hotel $j$ during year-month $t$, and 0 otherwise. In Equation (9), the dependent variable, $Response_{i,j,k,t}$, is a binary variable equal to 1 if a manager responds to a review rated by individual $i$ for the stay in year-month $t$ at hotel $j$ on website $k$, and 0 otherwise. Following Mudambi and Schuff (2010) and Liu and Park (2015), we include the count of sentence in a review to proxy the review depth in Equation (9). Keep in mind that only Expedia provides information on negative comments; and TripAdvisor and Expedia provide information on manager response. Therefore, the tests on Equations (8) and (9) are based on sub-samples. Similar to Equation (1), we control for year fixed effect and month fixed effect instead of the year-month fixed effect in Equations (8) and (9), because our interested variable, the monthly haze measurements, would be omitted if year-month fixed effect is included. Other fixed effects are the same as those in Equation (1).

Panel A (Columns 1 and 2) of Table 8 presents the results of estimating logit regression (8) and logit regression (9), respectively. In Column (1), the coefficient for $Shock^b$ is 0.749, which means that during the severe haze period, we expect 0.749 increase in the log-odds of the dependent variable *Negative.Comment*, holding all other independent variables constant, suggesting that reviewers are more likely to leave negative comments if they stay in hotel in the haze period. This is supportive of **H1**. We also use other measures of air pollution for robustness check and results are reported in Table B7 in Appendix B. We find all measures of air quality are positive and significant, except for *DoH*.

[**Table 8 inserted here**]

While managers' responses to online reviews play an important role in customer satisfaction, managers do not respond to every online review and may choose to pay particular attention to specific types of reviews (Park and Allen, 2013). Column (2) of Table 8 shows the estimation results examining the likelihood for hotel managers to respond to online reviews. The positive and significant coefficients on *ln(No. of sentences)* suggest that managers strategically respond to reviews written in longer sentences, which reflect the communication richness and sophistication of the comments. The coefficient on $Shock^b$ is positive and statistically significant at 0.171, implying that managers are more likely to respond to reviews of haze-episode stay. *Review Score* bears a significant and negative sign, indicating that reviews with lower scores are more likely to be responded by the hotel manager. The positive $Shock^b$ and negative *Review Score* support **H2** and **H3**, respectively. The results also provide evidence of crisis management due to environmental shocks. The results using other measures of air quality in estimating Equation (9) are reported in Table B8 in Appendix B.

Next, we test **H4** to see whether managers' responses affect hotels' review scores in the next period using the following specification:

$$Score_{j,k,t} = \alpha + \beta \cdot Response_{j,k,t-1} + \phi \cdot Haze_t + \gamma \cdot X_{t,l} + \eta_k + \zeta_j + \theta_{year} + \theta_{month} + \epsilon_{j,k,t} \tag{10}$$

where the dependent variable is the average online review score for hotel $j$ on website $k$ in year-month $t$. $Response_{j,k,t-1}$ refers to the total number of responses or the response rate (in percentage) for hotel $j$ on website $k$ in the previous period $t-1$.

Panel B (Columns 3 to 4) of Table 8 reports the results, with $Response_{j,k,t-1}$ in Column (3) being the logarithmic total number of responses and $Response_{j,k,t-1}$ in Column (4) being the response rate (in percentage). We find $Response_{j,k,t-1}$ is significantly positive in both columns, implying that responses to online reviews in the previous period lead to a positive increase in the online review score in the current period. The results indicate that managers' responses acknowledge the existing service issues, which allows management teams to address problems and increase customer satisfaction. We also conduct the tests using other measures of haze and report the results in Table B9 in Appendix. The results are consistent. Altogether, hoteliers largely improve their operations and services following a temporary negative shock to their online reputation due to exogenous pollution events, with the effect being stronger in hotels whose managers closely monitor their online reviews.

# 6 Alternative Explanations

This section addresses alternative explanations for improvements in the levels of service experienced by hotel guests that can raise the scores reflected by online reviews.

## 6.1 Unobserved Hotel-level Shocks: Planned Renovations or Training

The first possible explanation is service quality improvements that are related to hotel level shocks but not to ex-post haze shocks. For instance, if a hotel had already planned renovations before the haze shock, a rise in review scores after a haze episode might be related not to improved service levels but to a simultaneous hotel-level shock that enhances guests stay experiences. In theory, including the hotel-month fixed effects in Equation (2) (as reported in Table B10) would control for this kind of local shock. Since the results are similar to those of Table 3, the implication is that hotel-level shocks have only a minimal effect on the results.

## 6.2 Changes in the Hotel Sample: Newly-Built Luxury Hotels

The second concern relates to the inclusion in the sample of hotels, especially the higher quality ones, built after the haze shock. The impact would be relatively low review scores during haze shocks related to the absence of new hotels from the analysis. Therefore, the exclusion from the investigation of hotels built after 2012 avoids any related contamination of results. Furthermore, the DID tests focus on a two-year period to mitigate the possibility of hotel renovations. Including hotel fixed effect also relieves this concern.

## 6.3 Discounts on Room Prices and Changes in the Guest Quality

The third possible reason is that cutting room prices following a haze shock in a move to restore a hotel's reputation and lower customer churn could contribute to rising review scores since guests pay lower prices for the same service levels. Furthermore, decreasing room prices could also influence the quality of guests. For example, guests who previously stayed at four-star hotels could choose to move up to five-star hotels for the same room price. To determine whether this was a factor, we examine the monthly average room prices of all hotels provided by the Singapore government [20]and found that they did not in fact decrease following the haze shock (refer to the dotted in Figure 7), suggesting this alternative is not a concern. We also examined the government statistics on international visitors[21] (refer to Figure 7), which indicate no decline on the number of visitor arrivals after haze shocks. In fact, arrivals of international visitors even increased following the June 2013 haze shock. From the stability of room prices and international arrivals, we conclude that the quality of guests is unlikely to influence our findings.

## 6.4 Outliers in the Responses: Responses from Few Hotels

The fourth alternative explanation is the relatively low number of hotels that show significant response to haze shocks by improving quality of service to compensate for the negative guest experience. Standard linear regression techniques summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function E(y—x). This provides only a partial view of the relationship, as we might be interested in describing the relationship at different points in the conditional distribution of y. Quantile regression provides that capability (Koenker and Bassett Jr, 1982).

To provide more robust results against outliers in the responses measurement, we employ the quantile regression to estimate Equation (2) using the Jun 2013 haze shock. Specifically, as shown in Table B11, we find that the coefficient estimates for 25th, 50th, and 75th are positive and statistically significant, suggesting hotels in different quantiles respond to the haze shock. The results of quantile regressions provide us with a more comprehensive picture of the relationship between review score and haze shock ex-post the haze episode and show that our conclusions are not driven by the outliers or abnormal distributions of the hotel responses.

[20]The data source: https://data.gov.sg/dataset/monthly-gazetted-hotel-statistics-by-hotel-tier
[21]The data source: https://data.gov.sg/dataset/international-visitor-arrivals-by-country-of-nationality

### 6.5 Heterogeneous Reviewers

Although in this paper we assume reviewers to be homogenous, in fact of course individual travelers are different from each other. This realization raises another issue, which is that the travelers prior to a haze shock are significantly different from the travelers after a haze shock. To test for this phenomenon, we use a sample of only travelers who visit frequently by repeating the estimations following Equation (2). Here, "frequent travelers" is defined as travelers who visit Singapore both before and after a haze period. Included in the data of *TripAdvisor* is each reviewer's account ID, which allows us to conduct an analysis of haze shocks at the level of individuals. Table B12 shows the results, which indicate that after the haze shock, the total review score increases 0.48 points. According to the sub-category analysis, the only increases in value are the scores related to value and service. Therefore, the results are consistent with those of previous tables, suggesting that traveler heterogeneity before and after a haze does not impact the results of our study.

## 7 Heterogeneity and Falsification Tests

### 7.1 Heterogeneity Tests

In this section, we provide the heterogeneity tests across traveller types, travellers' country of origin, and hotel star rating. Specifically, Table 9 shows the heterogeneity in the responses of online review scores to the haze shock across traveller types and travellers' country of origin. As shown in Column (1), the interaction term, $Shock^b$*Business, is significantly negative, suggesting that business travellers are more sensitive to the haze shock relative to non-business ones. Economically, the severe haze shock led to a 0.417 points decrease in business travellers' review score, compared to a 0.335 points decrease in non-business travellers' review score. Column (2) reveals that Europeans are the most environmentally sensitive travellers, which is reflected by the largest decrease (-0.374) of review scores during the haze episode.

**[Table 9 inserted here]**

Managers' response to online reviews varies dramatically among hotels, regardless whether the hotels have similar guest ratings or whether the reviews are positive or negative (Levy et al., 2013; Park and Allen, 2013). Table 10 presents the heterogeneity in the responses of online review scores to the haze shock across hotel star ratings (Column 1), the heterogeneity in the responses of online review scores ex-post the haze shock across hotel star ratings (Column 2), and the heterogeneity in the manager response across hotel star ratings (Column 3). Column (1) shows that drops in the review scores of the reference group, one-star and two-star hotels, are greater than those of three-to five-star hotels during the haze period. In

Column (2), we can see that although the review scores of one- and two-star hotels scarcely changed ex-post the haze shock, the review scores of three- to five-star hotels rise significantly after the haze episode. Column (3) indicates that managers of four-star hotels are more likely to respond to the reviews that cover for a haze-episode stay than managers of non-four-star hotels. This suggests four-star hotels are more concerned about loss of reputation due to haze shocks.

**[Table 10 inserted here]**

### 7.2 Falsification Tests

We conduct a falsification test to further eliminate the concerns on omitted variable bias or unobserved shocks in our triple-differences specification. Specifically, we estimate Equation (7) during the pre-shock period (from Jun 2012 to Jun 2013) by assigning the weather shock in three different periods (Sep 2012, Dec 2012, and Mar 2013). Unless there were unobserved local shocks in these two regions before Jun 2013, the interaction terms in Equation (7) should have no effect on the review scores. As shown in Table B13, the coefficients of all six interactions are statistically insignificant and indifferent from zeros, suggesting that omitted variables and unobserved shocks are unlikely to be concerns in our study.

## 8 Welfare Analysis

An exogenous air pollution event in Singapore provides us with an opportunity to explore how consumers react to negative environmental shocks, and how the service sector might react to a temporary reputation crisis by improving service quality. Specifically, the types of responses in the review input from consumers suggest that their mood during the period of the visit was negatively affected by the pollution event rather than by concerns related to the quality of service they received. The substantial damage to the online reputations then triggers hotels to improve their service quality after the event, which subsequently raises customer satisfaction level, creating a virtuous circle that generates substantial economic gains.

Existing research has strived to utilize economic analysis to estimate the dollar benefits of air quality improvements. One approach is to proxy willingness to pay by measuring the additional cost to society from diminished air quality (Deschênes et al., 2017). The results in this paper allow us to conduct a simple welfare analysis. The welfare gains or losses in lodging experiences can occur in many forms. For example, gains can include the increased consumer satisfaction due to better service quality, superior lodging experiences due to better mood, or monetary savings from hotel room discounts, while losses can include the negative health-related consequences, disappointment or anxiety due to the air pollution, or perception of worse service quality. Our focus in this study is the consumers' subjective sense of their own well-being, namely customer satisfaction level as reflected by the online reviews scores.

In this section, we quantify the impacts of air pollution events on the changes of guests' subjective well-being both during and after the haze period. As illustrated in the dynamic analysis (as shown in Figure 5), the online review scores dropped substantially by around 0.47 points on average during the Jun 2013 haze episode, and then reverted to and even exceeded their previous levels immediately after the haze shock. The cost-benefit analysis calculates the welfare losses during air pollution period and the welfare gains from the improved services that triggered by the negative shock. Following Larcom et al. (2017), we define the welfare gain (or loss) from the increase (or decrease) in the guests' subjective well-being is as follows:

$$Average\ Gain = \frac{\sum_{t=0}^{n} Revenue_t \times \frac{\Delta Score_t}{Score_{sg,hk}}}{\sum_{t=0}^{n} Room_t} \tag{11}$$

where $t$ indexes the year-month. $Revenue_t$ stands for the total room revenue[22] of the hospitality industry in Singapore in year-month $t$. $\Delta Score_t$ refers to the coefficients obtained from the dynamic difference-in-differences estimation for year-month $t$, as shown in Figure 5. $Score_{sg,hk}$ stands for a constant number 7.77, which is the average review score of hotels in Singapore and Hong Kong during the benchmark period (from Jun 2012 to Nov 2012). Therefore, $\frac{\Delta Score_t}{Score_{sg,hk}}$ stands for the percentage change of the online review scores in year-month $t$ relative to the benchmark score. $\sum_{t=0}^{n} Revenue_t \times \frac{\Delta Score_t}{Score_{sg,hk}}$ estimates the total welfare change in the form of total room revenue between time $t$ and time $n$. Dividing the total welfare change by the number of gross occupied rooms between time $t$ and time $n$, $\sum_{t=0}^{n} Room_t$, we get the average welfare change per room per night.

Figure 7 depicts the welfare gains (or losses) in dollars during our DID sample period. The dark line indicates the entire path of dynamic response of the online review scores of hotels in Singapore to air pollution shock relative to the ex-ante benchmark review scores, using online reviews from hotels in Hong Kong as the control group. The white bar indicates the monthly total room revenue in millions of Singapore dollars.

**[Figure 7 inserted here]**

To illustrate, in June 2013, the relative change of score (in percentage) is (-0.476/7.77)=-6.13%, and the total room revenue is S$246.5 million. Ideally, in the absence of the air pollution shock, the guests should enjoy a benchmark subjective well-being of 7.77 by paying S$246.5 million. Due to the haze shock, the travellers' subjective well-being or relative

[22]Singapore Tourism Board (STB) provides monthly Gazetted Hotel Statistics, including the total room revenue, average room rate, average occupancy rate, gross occupied hotel rooms per month, etc., see https://data.gov.sg/dataset/monthly-gazetted-hotel-statistics-summary for more detail.

utility decreases by 6.13% compared to the counter-factual state, but they are still paying the same prices, which accounts for S$246.5 million in total. Therefore, the welfare losses due to the decrease in the guests' subjective well-being in the form of total room revenue are 246.5*6.13%=S$15.10 million. We further compute the average welfare loss for one occupied room per night during the haze episode by dividing the welfare gains in total room revenue by the number of total occupied hotel rooms in June 2013, which is (S$15.10 million/951,709)=S$15.86.

Similarly, we use total room revenue to compute the welfare gains reflected by the guests' increased subjective sense of well-being. For instance, the welfare gains in August 2013 are 258.1*(0.421/7.77)=S$13.99 million. That is, thanks to the improvements in service levels that took place after the haze shock, the guests enjoy (0.421/7.77)=5.42% more of the benchmark subjective well-being of 7.77 by paying S$258.1 million. Likewise, we can compute the welfare gains in the form of total room revenue for each of the 12 months after June 2013; the welfare gains or losses are indicated by the solid blue bar in Figure 7. The accumulated welfare gains in the 12 months after June 2013 are estimated at S$70.41 million. Dividing this figure by the number of gross occupied rooms during the period produces the averaged welfare gain for one room: (S$70.41 million/12,427,085)=S$5.67. In summary, one guest per night (assuming a guest occupies one room) experiences a S$15.86 welfare loss in June 2013 as a result of the haze shock, but then receives a S$5.67 welfare gain during the 12 months that follow.

# 9 Conclusion

This paper examines the effects of an exogenous weather shock on the performance of hotels and the subjective well-being of travelers during and after a haze episode. Using online review data collected from three prominent hotel-booking websites, the study shows that hotels' review scores dropped significantly during haze periods, and then immediately reverted to previous levels in the month following the shock. More interestingly, the review score continued to rise sharply in the second month after the haze episode, before starting to decline and finally reach a plateau with a score a little higher than the original level. Exogenous environmental shocks, such as serious haze episodes, significantly reduce the satisfaction level of tourists and negatively impact the online review scores of hotels during guests' stays. Moreover, the lower online review scores can be attributed to the negative moods or higher anxiety levels of guests, rather than to any lowering in the quality of hotel service.

By applying the difference-in-differences and triple-differences approaches that rely on subcategory review scores and reviews from two regions, we show that, following a temporary reputation crisis due to a negative environmental shock, most hoteliers improve their operations and services in order to restore their online image. Furthermore, this response being stronger in the cases of hotels with managers closely monitoring their online reviews during the haze episodes.

In particular, we show that the service quality (the customer satisfaction of improvable aspects) is significantly enhanced ex-post the haze shock, compared with that of non-improvable rating categories. This implies that without a threat to its online reputation, hotels fails to optimize its productivity by providing best services, as evidenced by ascending review scores after the haze periods.

We also consider changing review scores from the perspective of managers. Specifically, we demonstrate that managers are more likely to respond to reviews with lower scores and to reviews that cover a stay during a haze period. Our calculation indicates that responses to reviews contribute to a rise in review scores during the next period. The results, together with the subcategory results, suggest a channel used by hotels to improve their service level following a haze episode.

A growing body of literature has proved the negative impacts of various types of pollution on economic growth (Jorgenson and Wilcoxen, 1990), productivity (Chang et al., 2016), health (Deschênes et al., 2017), housing price (Chay and Greenstone, 2005), and many other areas. Our investigation focuses on the haze effects to the service sector and highlights another direction for pollution studies. We provide empirical evidence to show that detrimental environmental shocks could trigger positive outcomes by spurring hotels to improve service quality. This paper has policy implications related to deficiencies in hotel management for hoteliers as well as regulators. The computation of the welfare gains indicates that travellers in Singapore on average enjoy a service improvement estimated at S$5.67 per room per night in the subsequent 12 month following a haze shock.

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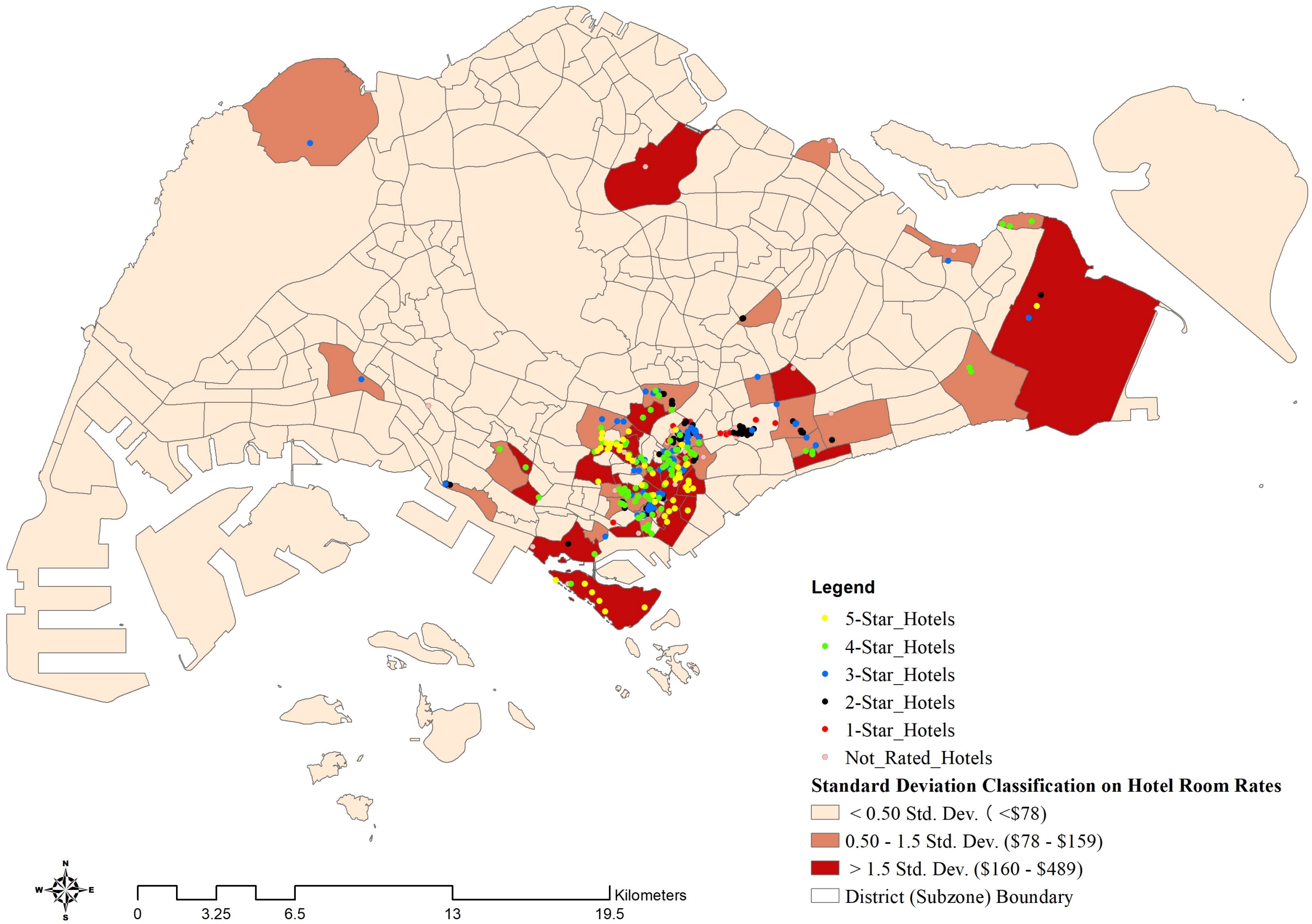
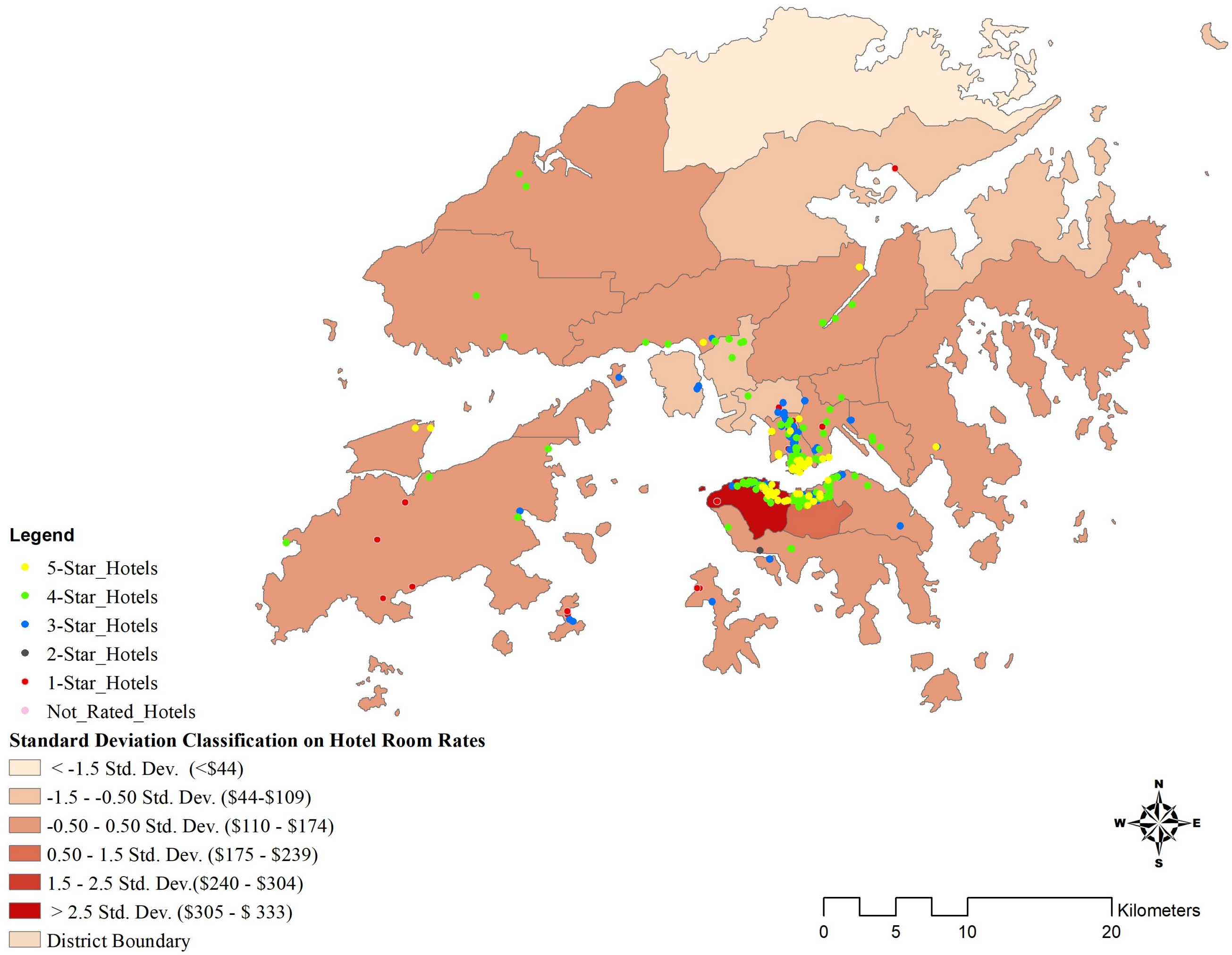
Figure 1: Geographic Distributions of Hotels by Star Rating in Singapore



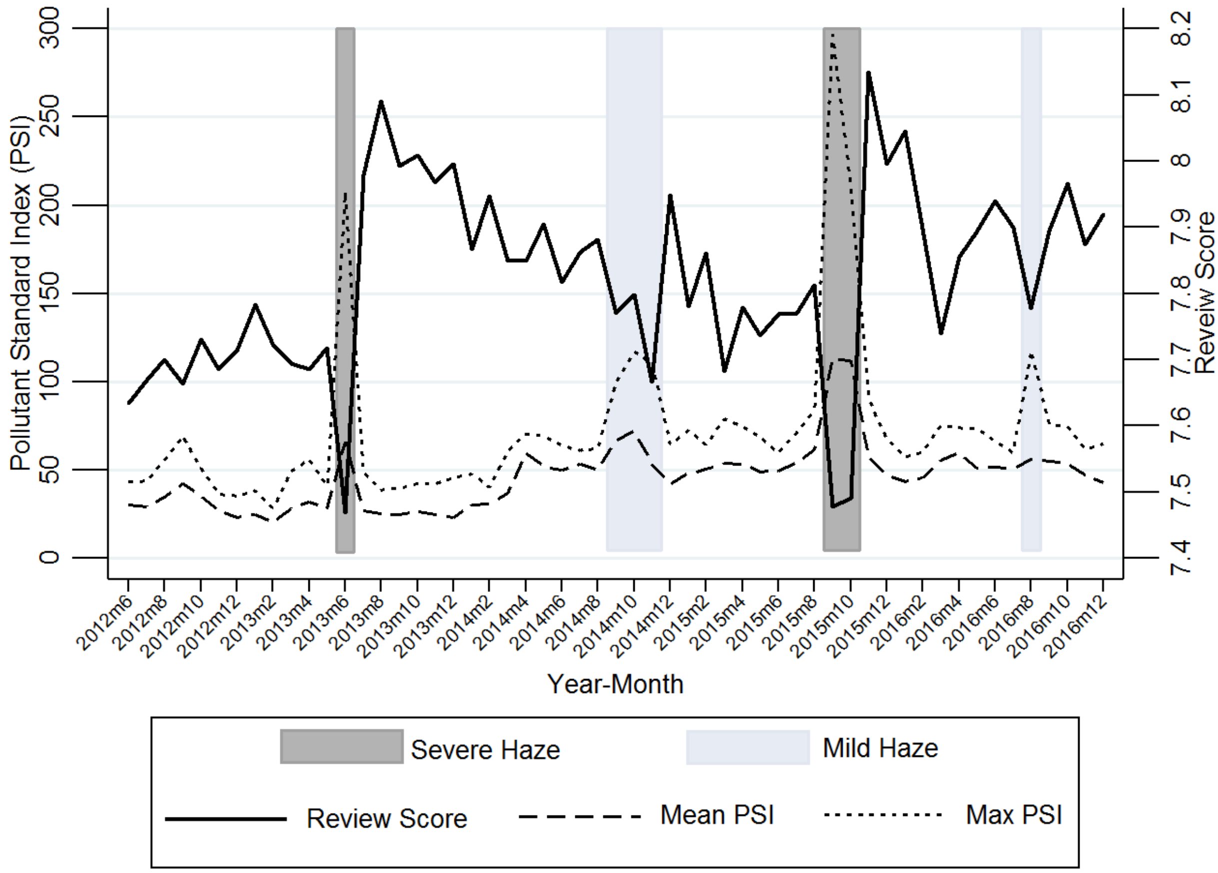

*Notes*: This figure plots the geographic distributions of hotels and hostels in Singapore by star rating. We plot the quantile distribution by hotel daily room prices at the neighborhood (sector) level.

Figure 2: Geographic Distributions of Hotels by Star Rating in Hong Kong



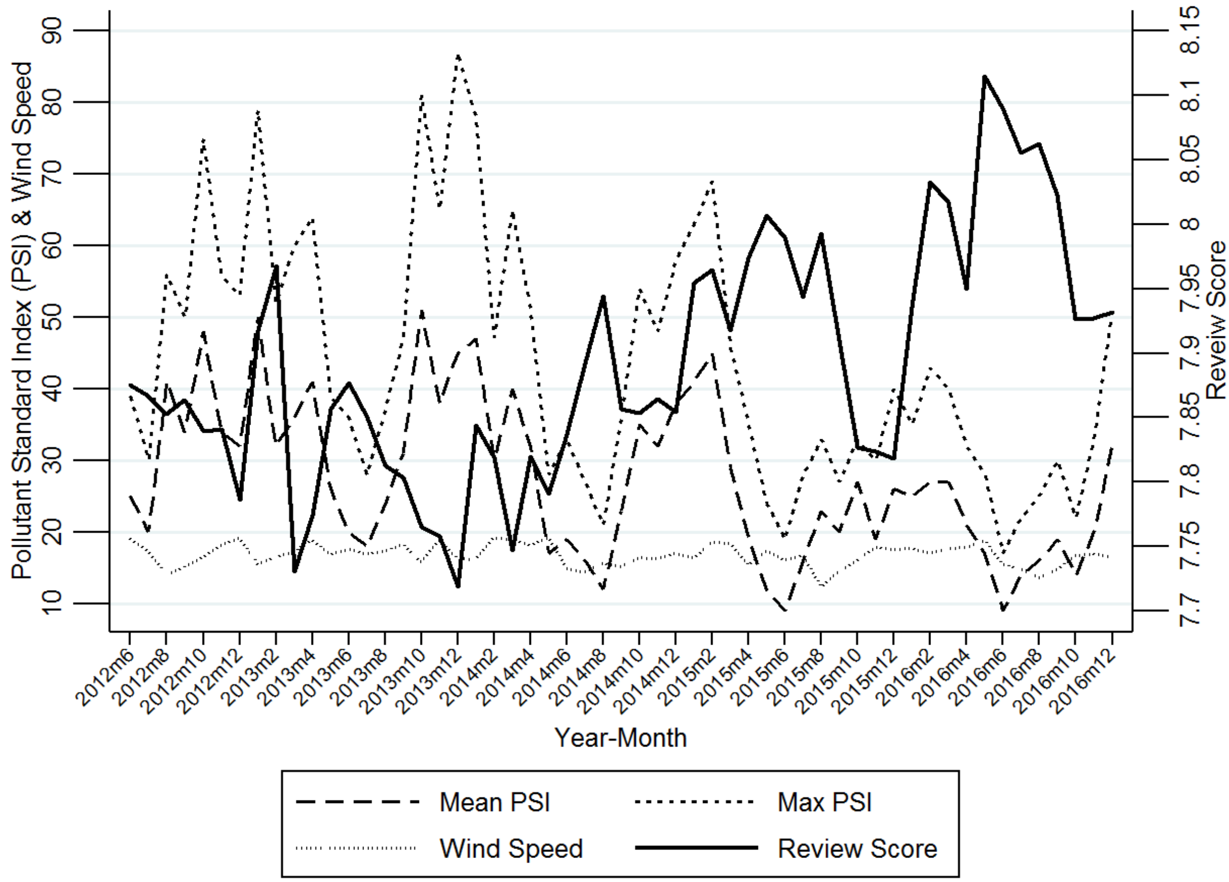

*Notes*: This figure plots the geographic distributions of hotels and hostels in Hong Kong by star rating. We plot the quantile distribution by hotel daily room prices at the neighborhood (sector) level.

Figure 3: Monthly Trends of Air Pollution Measures and Online Review Scores in Singapore



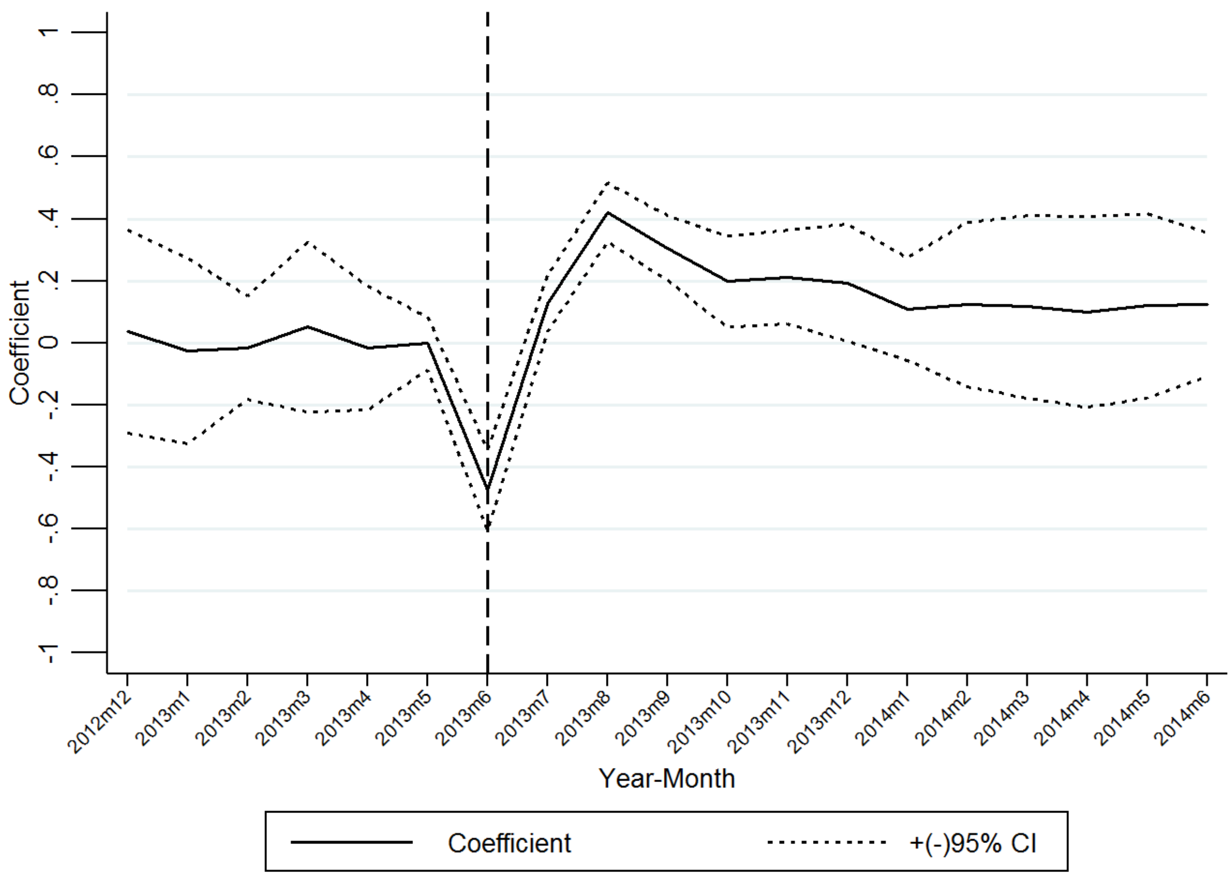

*Notes*: Figure 3 plots the monthly trends of mean PSI (dashed line) and maximum PSI (dotted line), as well as the average online review score of hotels from June 2012 to December 2016 in Singapore. The dark shaded areas and large spikes highlight two strong haze shocks in Jun 2013 and Sep-Oct 2015, while the light shaded areas represent two mild haze episodes in Oct 2014 and Aug 2016. The width of shaded areas indicates the duration of air pollution events.

Figure 4: Monthly Measures of Air Pollution, Wind Speed and Online Review Scores in Hong Kong



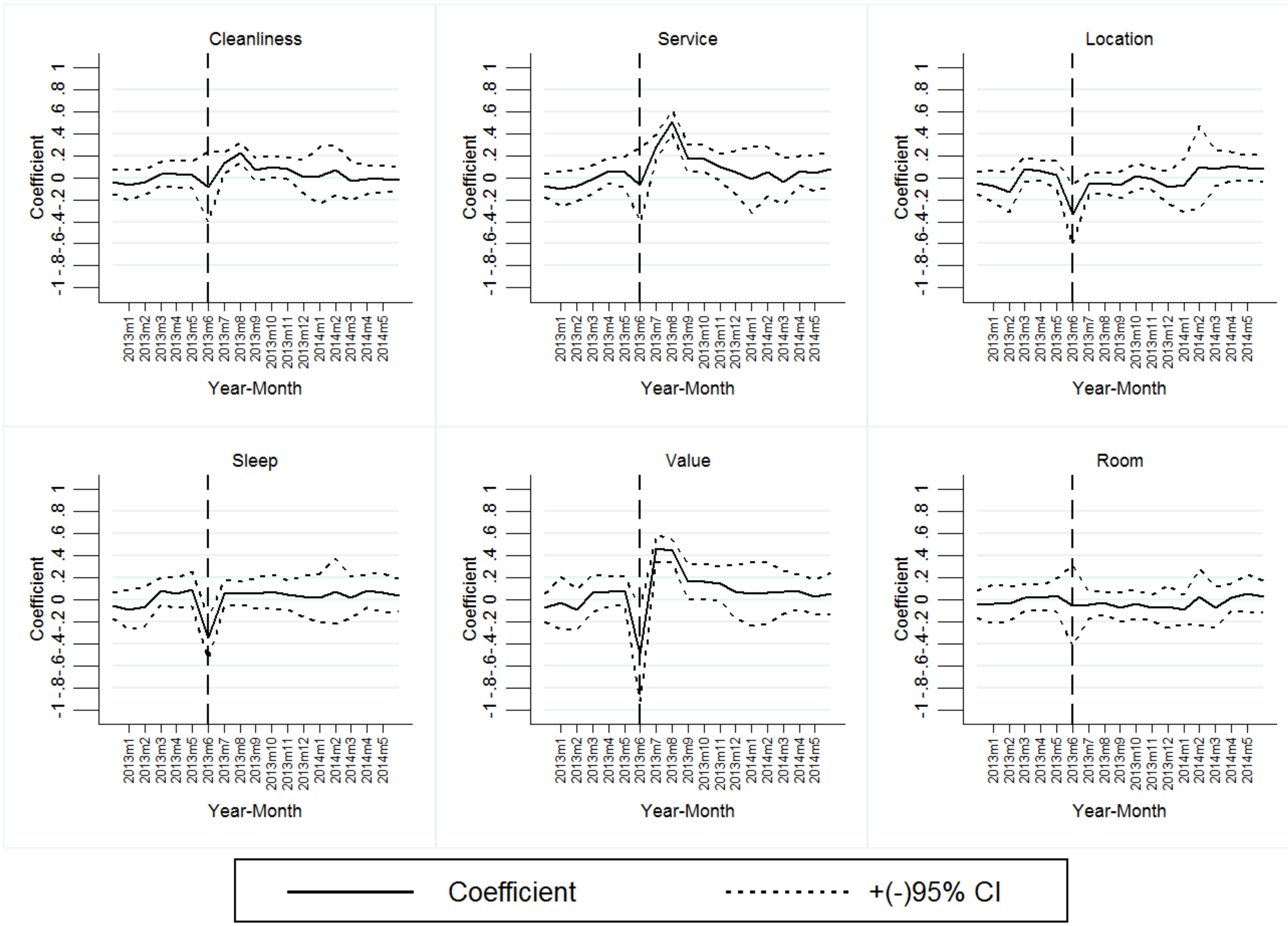

*Notes*: This figure plots the monthly trends of mean PSI (dashed line), maximum PSI (dotted line), wind speed, as well as the average online review score (solid line) of hotels in Hong Kong from June 2012 to December 2016.

Figure 5: Estimated Response Dynamics of Aggregate Review Scores



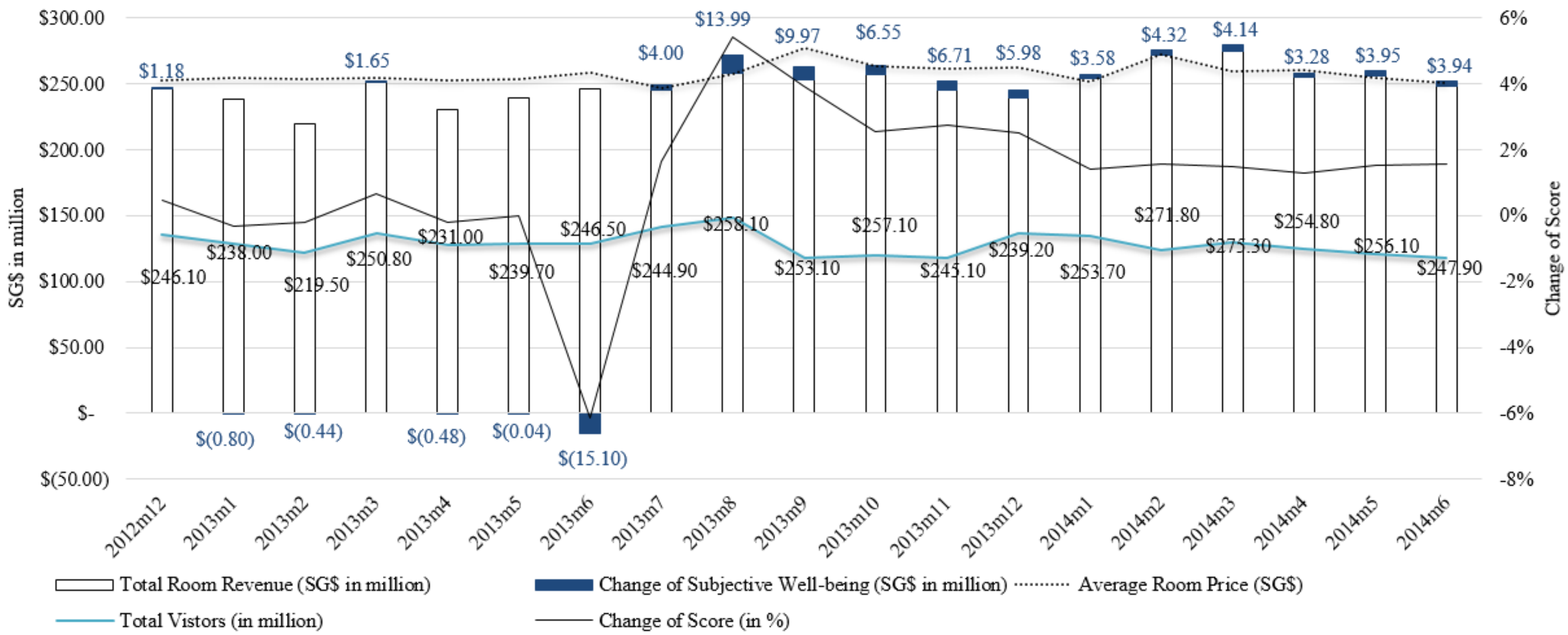

*Notes*: This figure plots the entire path of dynamic response of the aggregate online review scores of hotels in Singapore to the air pollution shock, along with its corresponding 95 percent confidence intervals. The x-axis denotes the year-month and y-axis shows the unit change on review scores.

Figure 6: Estimated Response Dynamics of Subcategory Review Scores




*Notes*: This figure plots the entire paths of dynamic responses of subcategory online review scores of hotels (*cleanliness*, *service*, *location*, *sleep quality*, *value*, and *room)* in Singapore to the air pollution shock, along with their corresponding 95 percent confidence intervals. The x-axis denotes the year-month and y-axis shows the unit change on review scores.

Figure 7: Welfare Analysis




*Notes*: This figure shows the welfare analysis. The dark line indicates the entire path of dynamic response of the online review scores of hotels in Singapore to air pollution shock relative to the ex-ante benchmark review scores, using online reviews from hotels in Hong Kong as the control group. The green line indicates the monthly arrivals of international investors. The dotted line indicates the monthly average room price of hotels in Singapore. The white bar indicates the monthly total room revenue in millions of Singapore dollars. The solid bar indicates the monthly welfare gains of losses in the form of total room revenue.

Table 1: Descriptive Staitstics

**Panel A: Online Reviews and Manager Responses**

| Country | Websites | Variables | Obs. | Mean | Median | S.D | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Singapore | *TripAdvisor, Agoda, Expedia* | Review Scores | 621,251 | 7.88 | 8.00 | 1.74 | 1.50 | 10.00 |
| | *TripAdvisor, Expedia* | Manager Responses | 246,890 | 0.51 | 1.00 | 0.50 | 0.00 | 1.00 |
| | *Expedia* | Negative Comments | 58,230 | 0.26 | 0.00 | 0.44 | 0.00 | 1.00 |
| Hong Kong | *TripAdvisor, Agoda, Expedia* | Review Scores | 562,046 | 7.89 | 8.00 | 1.68 | 2.00 | 10.00 |
| | *TripAdvisor, Expedia* | Manager Responses | 188,731 | 0.40 | 0.00 | 0.49 | 0.00 | 1.00 |
| | *Expedia* | Negative Comments | 62,966 | 0.21 | 0.00 | 0.41 | 0.00 | 1.00 |

**Panel B: Weather and Pollution**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Singapore | | Max PSI | 55 | 72.43 | 63.80 | 45.73 | 28.60 | 296.60 |
| | | Mean PSI | 55 | 46.08 | 48.02 | 18.57 | 20.33 | 112.44 |
| | | Days of Haze (*DoH*) | 55 | 1.49 | 0.00 | 3.94 | 0.00 | 20.00 |
| | | Temperature | 55 | 28.01 | 28.20 | 0.77 | 26.20 | 29.40 |
| | | Rainfall | 55 | 156.61 | 126.60 | 92.43 | 0.20 | 395.20 |
| | | Wind | 55 | 10.49 | 10.22 | 3.25 | 4.18 | 18.84 |
| | | Visibility | 55 | 9.17 | 9.35 | 0.79 | 5.64 | 9.85 |
| Hong Kong | | Max PSI | 55 | 43.73 | 39.00 | 17.66 | 17.00 | 87.00 |
| | | Mean PSI | 55 | 26.98 | 26.00 | 10.91 | 9.00 | 51.00 |
| | | Days of Haze (*DoH*) | 55 | 0.89 | 0.00 | 1.65 | 0.00 | 8.00 |
| | | Temperature | 55 | 24.75 | 26.54 | 5.06 | 15.58 | 30.77 |
| | | Rainfall | 55 | 212.91 | 148.70 | 186.35 | 1.50 | 687.30 |
| | | Wind | 55 | 16.79 | 16.89 | 1.57 | 12.35 | 19.22 |
| | | Visibility | 55 | 9.45 | 9.56 | 0.80 | 7.28 | 11.10 |

*Notes*: This table presents a summary description of our data set, with online review data at the individual level reported in Panel A, and ambient conditions on a monthly basis reported in Panel B. The sample period is from Jun 2012 to Dec 2016. Please refer to Appendix A for the definition of key variables.

Table 2: Responses of Online Review Scores to the Air Pollution Shocks from June 2012 to December 2016

| Haze Measure | $Shock^a$ | $Shock^b$ | $ln(PSI^{max})$ | $ln(PSI^{mean})$ | $DoH$ | PSI Category |
|---|---|---|---|---|---|---|
| Model | (1) | (2) | (3) | (4) | (5) | (6) |
| Haze | -0.268*** | -0.351*** | -0.278*** | -0.264*** | -0.031*** | |
| | (0.016) | (0.048) | (0.030) | (0.020) | (0.003) | |
| PSI_{61-120} | | | | | | -0.039*** |
| | | | | | | (0.012) |
| PSI_{above 120} | | | | | | -0.382*** |
| | | | | | | (0.050) |
| ln(Temperature) | 0.095*** | 0.046*** | 0.073*** | 0.090*** | 0.043*** | 0.053*** |
| | (0.010) | (0.010) | (0.011) | (0.011) | (0.009) | (0.011) |
| ln(Wind) | 0.010*** | 0.016*** | 0.017*** | 0.020*** | 0.011*** | 0.019*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(Rainfall) | -0.001 | -0.016*** | -0.000 | -0.002 | -0.017*** | -0.010** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| ln(Visibility) | 0.080*** | 0.044*** | 0.088*** | 0.046*** | -0.005 | 0.041*** |
| | (0.006) | (0.013) | (0.008) | (0.009) | (0.013) | (0.013) |
| Constant | 3.556*** | 5.417*** | 5.003*** | 4.912*** | 6.072*** | 5.168*** |
| | (0.316) | (0.281) | (0.289) | (0.293) | (0.298) | (0.298) |
| Observations | 621,251 | 621,251 | 621,251 | 621,251 | 621,251 | 621,251 |
| R-squared | 0.199 | 0.198 | 0.199 | 0.199 | 0.199 | 0.199 |
| Year and Month FE | YES | YES | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO | NO | NO |
| Country of Origin FE | YES | YES | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES | YES | YES |

*Notes*: This table presents the regression results of estimating Equation (1) using hotel online review data in Singapore from June 2012 to December 2016. The dependent variable is review score. Six different measures of air pollutants are used in the analysis. $Shock^a$ identifies all four haze shocks during the period, $Shock^b$ represents two severe shocks in Jun 2013 and Sep-Oct 2015, $DoH$ measures the number of days per month with haze status, and $PSICategory$ classifies the monthly average $PSI^{max}$ into three categories: 0-60, 61 to 120, and above 120. Year, month, guests' country of origin, website, guest type, and hotel fixed effects are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table 3: Ex-ante versus Ex-Post Responses of Online Review Scores

| Event | **Jun 2013 Haze** | | **Sep-Oct 2015 Haze** | |
|---|---|---|---|---|
| Post vs. Pre Period | *Period 2 vs. Period 1* | *Period 3 vs. Period 1* | *Period 4 vs. Period 3* | *Period 4 vs. Period 1* |
| Model | (1) | (2) | (3) | (4) |
| Post | 0.224*** | 0.098 | 0.216*** | 0.247*** |
| | (0.028) | (0.128) | (0.032) | (0.037) |
| ln(Temperature) | 0.124*** | -0.042 | 0.101*** | 0.027 |
| | (0.022) | (0.111) | (0.022) | (0.019) |
| ln(Wind) | -0.008* | 0.007 | -0.009 | -0.005 |
| | (0.004) | (0.013) | (0.007) | (0.003) |
| ln(Rainfall) | 0.015** | -0.024* | -0.021** | -0.012 |
| | (0.006) | (0.014) | (0.009) | (0.011) |
| ln(Visibility) | 0.014 | 0.135 | -0.160*** | -0.054* |
| | (0.021) | (0.250) | (0.055) | (0.028) |
| Constant | 3.280*** | 7.166*** | 7.189*** | 7.308*** |
| | (0.569) | (1.294) | (0.649) | (0.680) |
| Observations | 299,882 | 236,901 | 251,487 | 286,452 |
| R-squared | 0.207 | 0.207 | 0.195 | 0.201 |
| Year and Month FE | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO |
| Country of Origin FE | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES |

*Notes*: This table provides the estimation for the model specification 2. The coefficients on *Post* show the differences between the online review scores before and after two severe haze shocks. The dependent variable is review score. we divide the sample period into four periods: Jun 2012 to May 2013 (period 1, the pre-shock period of the Jun 2013 haze), Jul 2013 to Aug 2014 (period 2, the post-shock period of the Jun 2013 haze), Dec 2014 to Aug 2015 (period 3, the pre-shock period of the Sep-Oct 2015 haze), and Nov 2015 to Dec 2016 (period 4, the post-shock period of the Sep-Oct 2015 haze). Year, month, guests' country of origin, website, guest type, and hotel fixed effects are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table 4: DID Estimations: The Impact of the Haze Shocks on Online Review Scores

(Singapore VS. Hong Kong from June 2012 to August 2014)

| Haze Measure<br>Model | $Shock^b$<br>(1) | $ln(PSI^{mean})$<br>(2) | $ln(PSI^{max})$<br>(3) | $DoH$<br>(4) |
|---|---|---|---|---|
| Haze | 0.096*** | 0.092*** | -0.093*** | -0.011*** |
| | (0.024) | (0.016) | (0.022) | (0.004) |
| $Treatment_c$*Haze | -0.408*** | -0.266*** | -0.149*** | -0.046*** |
| | (0.038) | (0.026) | (0.026) | (0.005) |
| ln(Temperature) | -0.007*** | -0.014*** | -0.013*** | -0.003 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(Wind) | 0.010*** | 0.006*** | 0.013*** | 0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(Rainfall) | -0.010*** | -0.015*** | -0.028*** | -0.018*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| ln(Visibility) | 0.011 | 0.084*** | 0.012 | -0.046*** |
| | (0.011) | (0.008) | (0.011) | (0.012) |
| Constant | 7.416*** | 7.167*** | 8.292*** | 7.900*** |
| | (0.181) | (0.183) | (0.226) | (0.193) |
| Observations | 585,967 | 585,967 | 585,967 | 585,967 |
| R-squared | 0.207 | 0.207 | 0.207 | 0.207 |
| Year and Month FE | NO | NO | NO | NO |
| Year-Month FE | YES | YES | YES | YES |
| Country of Origin FE | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES |

*Notes*: This table reports the effects of severe air pollution events to online review scores from Jun 2012 to Aug 2014 using a difference-in-differences estimation (3). The treatment sample consists of all the online reviews on hotels in Singapore and the control sample consists of online reviews of hotels in Hong Kong. The dependent variable is review score. $Treatment_c$ is a binary variable equal to 1 for online reviews of hotels in Singapore, and is equal to 0 for online reviews of hotels in Hong Kong. Column 1 uses $Shock^b$ to indicate the Jun 2013 haze as both $Shock^a$ and $Shock^b$ stand for the Jun 2013 haze shock during the sample period. Year-month, guests' country of origin, website, guest type, and hotel fixed effects are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table 5: DID Estimations: Ex-ante versus Ex-Post Responses of Online Review Scores

(Singapore VS. Hong Kong from June 2012 to August 2014)

| Pre-shock period<br>Post-shock period<br>Model | -9 Months<br>+12 Months<br>(1) | -6 Months<br>+12 Months<br>(2) | -3 Months<br>+12 Months<br>(3) |
|---|---|---|---|
| $Treatment_c * Pre$ | 0.044 | 0.012 | 0.029 |
| | (0.027) | (0.022) | (0.026) |
| $Treatment_c * Post$ | 0.279*** | 0.256*** | 0.256*** |
| | (0.030) | (0.025) | (0.022) |
| ln(Temperature) | -0.184*** | -0.148*** | -0.142*** |
| | (0.043) | (0.041) | (0.042) |
| ln(Wind) | -0.024 | -0.027 | -0.016 |
| | (0.017) | (0.017) | (0.018) |
| ln(Rainfall) | 0.004 | 0.006** | 0.007** |
| | (0.003) | (0.003) | (0.003) |
| ln(Visibility) | 0.014 | 0.005 | 0.004 |
| | (0.011) | (0.011) | (0.011) |
| Constant | 7.899*** | 7.858*** | 7.821*** |
| | (0.185) | (0.189) | (0.183) |
| Observations | 559,695 | 559,695 | 559,695 |
| R-squared | 0.207 | 0.207 | 0.207 |
| Year and Month FE | NO | NO | NO |
| Year-Month FE | YES | YES | YES |
| Country of Origin FE | YES | YES | YES |
| Website FE | YES | YES | YES |
| Guest Type FE | YES | YES | YES |
| Hotel FE | YES | YES | YES |

*Notes*: This table reports the results of the changes of online review scores by applying Equation (4). $Treatment_c$ is a binary variable equal to 1 for online reviews of hotels in Singapore, and is equal to 0 for online reviews of hotels in Hong Kong. *Pre* is a binary variable equal to 1 for the months before the June 2013 haze shock, and *Post* is a binary variable equal to 1 for twelve months after the haze shock. The coefficients on *Treatmentc*Pre* show the differences in online review scores between hotels in Singapore and Hong Kong in the pre-shock period compared to the first month in the sample period. Year-month, guests' country of origin, website, guest type, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table 6: Changes on Subcategory Review Scores

| Subcategory | Cleanliness | Service | Location | Sleep Quality | Value | Rooms |
|---|---|---|---|---|---|---|
| Model | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Relationship of Subcategory Review Scores and Air Pollution Measures* | | | | | | |
| *Shock*[b] | -0.086 | -0.040 | -0.191** | -0.244* | -0.255* | -0.098 |
| | (0.099) | (0.106) | (0.094) | (0.136) | (0.138) | (0.141) |
| Constant | 10.417*** | 10.046*** | 8.149*** | 9.351*** | 8.498*** | 6.721*** |
| | (0.704) | (0.678) | (0.817) | (0.786) | (0.899) | (0.750) |
| Observations | 86,811 | 123,623 | 86,777 | 86,155 | 86,779 | 86,274 |
| $R^2$ | 0.171 | 0.138 | 0.221 | 0.162 | 0.089 | 0.221 |
| *Panel B: The Ex-post Responses of Subcategory Review Scores to the Haze Shocks* | | | | | | |
| *Post* | 0.148** | 0.357*** | 0.004 | 0.018 | 0.169*** | 0.007 |
| | (0.062) | (0.062) | (0.055) | (0.060) | (0.063) | (0.058) |
| Constant | 10.257*** | 9.317*** | 7.784*** | 9.892*** | 7.751*** | 6.373*** |
| | (1.006) | (1.265) | (1.123) | (1.420) | (1.614) | (1.288) |
| Observations | 48,423 | 52,784 | 48,319 | 48,037 | 48,212 | 48,167 |
| $R^2$ | 0.195 | 0.164 | 0.233 | 0.179 | 0.103 | 0.251 |
| Weather Control | Temperature, Wind, Rainfall, Visibility | | | | | |
| Fixed Effects | Year, Month, Country of Origin, Website, Guest Type, Hotel FE | | | | | |

*Notes*: This table presents the results estimating the impact of severe air pollution events on subcategory review scores. The dependent variable is the subcategory review score. Panel A examines the changes of subcategory review scores during the severe haze episodes, and Panel B compares the subcategory review scores between the post-shock and pre-shock periods. Year, month, guests' country of origin, website, guest type, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table 7: Ex-ante versus Ex-Post Responses of Subcategory Review Scores

| Test | **Panel A: DID Estimation** | | | **Panel B: DDD Estimation** | | |
|---|---|---|---|---|---|---|
| Region | **(SG Only)** | | | **(SG & HK)** | | |
| Pre- and Post- Period | -9m,+12m | -6m,+12m | -3m,+12m | -9m,+12m | -6m,+12m | -3m,+12m |
| Model | (1) | (2) | (3) | (4) | (5) | (6) |
| $Treatment_c * Treatment_p * Pre$ | | | | -0.064 | -0.074 | -0.057 |
| | | | | (0.062) | (0.062) | (0.066) |
| $Treatment_c * Treatment_p * Post$ | | | | 0.215*** | 0.215*** | 0.215*** |
| | | | | (0.051) | (0.051) | (0.051) |
| $Treatment_c * Pre$ | | | | 0.040 | 0.030 | 0.054 |
| | | | | (0.043) | (0.036) | (0.039) |
| $Treatment_c * Post$ | | | | 0.169*** | 0.161*** | 0.164*** |
| | | | | (0.038) | (0.036) | (0.033) |
| $Treatment_p * Pre$ | 0.033 | 0.001 | 0.014 | 0.037 | 0.034 | 0.033 |
| | (0.026) | (0.022) | (0.024) | (0.046) | (0.042) | (0.041) |
| $Treatment_p * Post$ | 0.276*** | 0.251*** | 0.254*** | 0.026 | 0.021 | 0.026 |
| | (0.044) | (0.038) | (0.034) | (0.047) | (0.043) | (0.041) |
| Constant | 7.689*** | 7.714*** | 7.711*** | 6.675*** | 6.649*** | 6.632*** |
| | (0.507) | (0.509) | (0.507) | (0.286) | (0.282) | (0.295) |
| Observations | 261,787 | 261,787 | 261,787 | 429,881 | 429,881 | 429,881 |
| R-squared | 0.176 | 0.176 | 0.176 | 0.703 | 0.703 | 0.703 |
| Control for Weather | NO | NO | NO | YES | YES | YES |
| Year and Month FE | NO | NO | NO | NO | NO | NO |
| Year-Month FE | YES | YES | YES | YES | YES | YES |
| Country of Origin FE | YES | YES | YES | YES | YES | YES |
| Sub-Category FE | YES | YES | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES | YES | YES |

*Notes*: Panel A studies the difference in the responses of subcategory online review scores (e.g., improvable category and non-improvable category) to the air pollution for hotels in Singapore using the difference-in-differences Equation (6). Panel B utilizes hotel reviews in both Singapore and Hong Kong and compares the haze effects to improvable and non-improvable categories using the triple differences Equation (7). Weather control variables, Year-month, guests' country of origin, website, guest type, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table 8: Negative Comments, Managers' Responses, and Changes on Review Scores

| Equation | **Panel A: Equations (8) and (9)** | | **Panel B: Equation (10)** | |
|---|---|---|---|---|
| Dependent variable | Neg. Comment | Manager Response | Review Score | Review Score |
| Model | (1) | (2) | (3) | (4) |
| *Shock*$^b$ | 0.749*** | 0.171*** | -0.484*** | -0.485*** |
| | (0.197) | (0.031) | (0.159) | (0.159) |
| Review Score | | -0.036*** | | |
| | | (0.003) | | |
| ln(no. of sentences) | | 0.051*** | | |
| | | (0.009) | | |
| Response_{t-1} | | | 0.051*** | 0.099* |
| | | | (0.018) | (0.058) |
| Constant | -3.420** | -0.273 | 4.165*** | 4.182*** |
| | (1.433) | (1.023) | (0.901) | (0.901) |
| Observations | 57,908 | 227,879 | 12,398 | 12,398 |
| R-squared | 0.273 | 0.198 | 0.541 | 0.541 |
| Control for Weather | YES | YES | YES | YES |
| Year and Month FE | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO |
| Origin Country FE | YES | YES | NO | NO |
| Website FE | YES | YES | YES | YES |
| Guest Type FE | YES | YES | NO | NO |
| Hotel FE | YES | YES | YES | YES |

*Notes*: Column 1 studies the likelihood of reviewers leaving negative comments during haze episodes following Equation (8). The dependent variable $Negative.Comment_{i,j,t}$ is a binary variable equal to 1 for a traveller to leave a negative comment if he/she stays in the hotel $j$ during the haze period $t$, and 0 otherwise. Column 2 examines the likelihood of hotel managers responding to online reviews during haze episodes. The dependent variable is a binary variable equal to 1 if a manager responds to a review rated by individual $i$ for the stay in year-month $t$ at hotel $j$ on website $k$, and 0 otherwise. Columns 3 and 4 study the impact of managers' responses on hotel review scores in the next period using the following specification (10). The dependent variable is the average online review score for hotel $j$ on website $k$ in year-month $t$. $Response_{j,k,t-1}$ refers to the logarithmic total number of responses (in Column 3) or the response rate in percentage (in Column 4) in the previous period $t-1$. Weather control variables, Year, month, guests' country of origin, website, guest type, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table 9: Heterogeneity Test by Reviewer Type

| Group | By traveller type | By continent |
|---|---|---|
| Model | (1) | (2) |
| $Shock^b$ | -0.335*** | -0.103 |
| | (0.049) | (0.138) |
| *Type of Travellers* | | |
| $Shock^b$ * Business | -0.082*** | |
| | (0.027) | |
| *Continent of Origin* | | |
| $Shock^b$ * Africa | | -0.064 |
| | | (0.200) |
| $Shock^b$ * Asia | | -0.026 |
| | | (0.122) |
| $Shock^b$ * Europe | | -0.271** |
| | | (0.127) |
| $Shock^b$ * North America | | -0.234* |
| | | (0.127) |
| $Shock^b$ * Oceania | | -0.218** |
| | | (0.122) |
| Constant | 5.408*** | 5.352*** |
| | (0.290) | (0.291) |
| Observations | 621,251 | 621,251 |
| R-squared | 0.201 | 0.198 |
| Control for Weather | YES | YES |
| Year and Month FE | YES | YES |
| Year-Month FE | NO | NO |
| Origin Country FE | YES | YES |
| Website FE | YES | YES |
| Guest Type FE | YES | YES |
| Hotel FE | YES | YES |

*Notes*: This table shows reviewer type heterogeneity in the online review scores responses in the full sample period. The dependent variable is the review score. Column1 studies the difference in response between business travellers and non-business travellers. Column 2 examines the difference in response of travellers by continent of origin. Weather control variables, Year, month, guests' country of origin, website, guest type, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** $p<0.01$, ** $p<0.05$,* $p<0.1$.

Table 10: Heterogeneity Test by Hotel Star Rating

| Dependent Variable<br>Model | Review Score<br>(1) | Review Score<br>(2) | Manager Response<br>(3) |
|---|---|---|---|
| *Shock*$^b$ | -0.384*** | | -0.589 |
| | (0.050) | | (0.399) |
| *Post* | | 0.015 | |
| | | (0.038) | |
| <u>*Hotel Star Rating*</u> | | | |
| *Shock*$^b$ * star3 | -0.119*** | | 0.813* |
| | (0.039) | | (0.449) |
| *Shock*$^b$ * star4 | 0.029 | | 0.921** |
| | (0.038) | | (0.417) |
| *Shock*$^b$ * star5 | 0.100** | | 0.657** |
| | (0.042) | | (0.313) |
| *Post* * star3 | | 0.194*** | |
| | | (0.047) | |
| *Post* * star4 | | 0.271*** | |
| | | (0.038) | |
| *Post* * star5 | | 0.193*** | |
| | | (0.034) | |
| Review Score | | | -0.036** |
| | | | (0.015) |
| ln(No. of sentences) | | | 0.051*** |
| | | | (0.003) |
| Constant | 5.339*** | 3.197*** | -0.270 |
| | (0.281) | (0.583) | (0.775) |
| Observations | 621,168 | 299,847 | 227,879 |
| R-squared | 0.199 | 0.214 | 0.192 |
| Control for Weather | YES | YES | YES |
| Year and Month FE | YES | YES | YES |
| Year-Month FE | NO | NO | NO |
| Country of Origin FE | YES | YES | YES |
| Website FE | YES | YES | YES |
| Guest Type FE | YES | YES | YES |
| Hotel FE | YES | YES | YES |

*Notes*: This table shows hotel rating heterogeneity in the online review scores and manager responses. Column 1 examines the impact of severe haze episodes on review scores by hotel star rating. Column 2 compares the changes of online review scores before and after the haze shock. Column 3 shows the likelihood of manager responses during the severe haze shock by hotel star rating. The benchmark group includes hostels without rating and hotels rated as 1 or 2 stars. Weather control variables, Year, month, guests' country of origin, website, guest type, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

# Appendices

### Appendix A. The Definitions of Variables

*Review Score*: the aggregate review score made by a guest on the hotel-booking website after his/her stay at the hotel, which is used to grade the guest's experience in the hotel. The review score in *TripAdvisor.com* ranges from 0 to 10, which is the average of sub-scores of six components: cleanliness, service, location, sleep quality, value, and room. The review score in *Agoda.com* and *Expedia.com* ranges from 0 to 5. For interpretation and consistency, we rescale the review score in *Agoda.com* and *Expedia.com* to 0 to 10. The higher score corresponds to a better feed back or better evaluation on the guest's stay at the hotel.

*Cleanliness*: the subcategory review score made by a guest on the *TripAdvisor.com* website after his/her stay at the hotel, which is used to grade the cleanliness of the hotel.

*Service*: the subcategory review score made by a guest on the *TripAdvisor.com* website after his/her stay at the hotel, which is used to grade the service quality of the hotel.

*Location*: the subcategory review score made by a guest on the *TripAdvisor.com* website after his/her stay at the hotel, which is used to grade the location of the hotel.

*Sleep*: the subcategory review score made by a guest on the *TripAdvisor.com* website after his/her stay at the hotel, which is used to grade the guest's sleep quality of the hotel.

$Value$: the subcategory review score made by a guest on the *TripAdvisor.com* website after his/her stay at the hotel, which is used to grade the value of the hotel.

*Room*: the subcategory review score made by a guest on the *TripAdvisor.com* website after his/her stay at the hotel, which is used to grade the room of the hotel.

$Manager\ Response$: is a binary that equals 1 if the hotel manager responds to a review, and 0 otherwise. Only TripAdvisor.com and Expedia provide the information on Response.

$Negative\ Comment$: is short for negative comment. It is a binary variable that equals 1 if the guest leaves a negative comment after his/her stay at the hotel, and 0 otherwise. Only Expedia provides the information on Response.

$PSI^{max}$: is the maximum value of the daily PSI in a month.

$PSI^{mean}$: is the mean value of daily PSI in a month.

$DoH$: is the number of days that experience haze in a month.

$Temperature$: is the average value of daily temperature in a month.

$Rainfall$: is the total milliliter of rainfall in a month.

$Wind$: is the mean value of the daily speed of wind in a month.

$Visibility$: is a measure of the distance (in kilometre) at which an object or light can be clearly discerned.

$Shock^a$: is a binary variable equals to 1 if the guest/reviewer stayed at the hotel during the any of the four haze shocks (as shown in Figure 2).

$Shock^b$: is a binary variable equals to 1 if the guest/reviewer stayed at the hotel during the any of the two heavy haze shocks.

$PSI_{0-60}$: is a binary variable that equals 1 if the Max PSI ranges from 0-60.

$PSI_{61-120}$: is a binary variable that equals 1 if the Max PSI ranges from 61-120.

$PSI_{above120}$: is a binary variable that equals 1 if the Max PSI is higher than 120.

*Response_(t-1)*: is the number of response (or the rate of of response) for a hotel in month $t-1$.

$Treatment_C$: is a binary variable that equals 1 if the review score is on the hotels that are located in Singapore, and 0 if the review score is on the hotels that are located in Hong Kong.

$Treatment_T$: is a binary variable that equals 1 if the sub category review score is on cleanliness and service, and 0 if the sub category review score is on location, sleep quality and room.

$Pre$: is a binary variable that equals 1 if the review is made by a guest for his/her stay before the haze shock in 2013 m6.

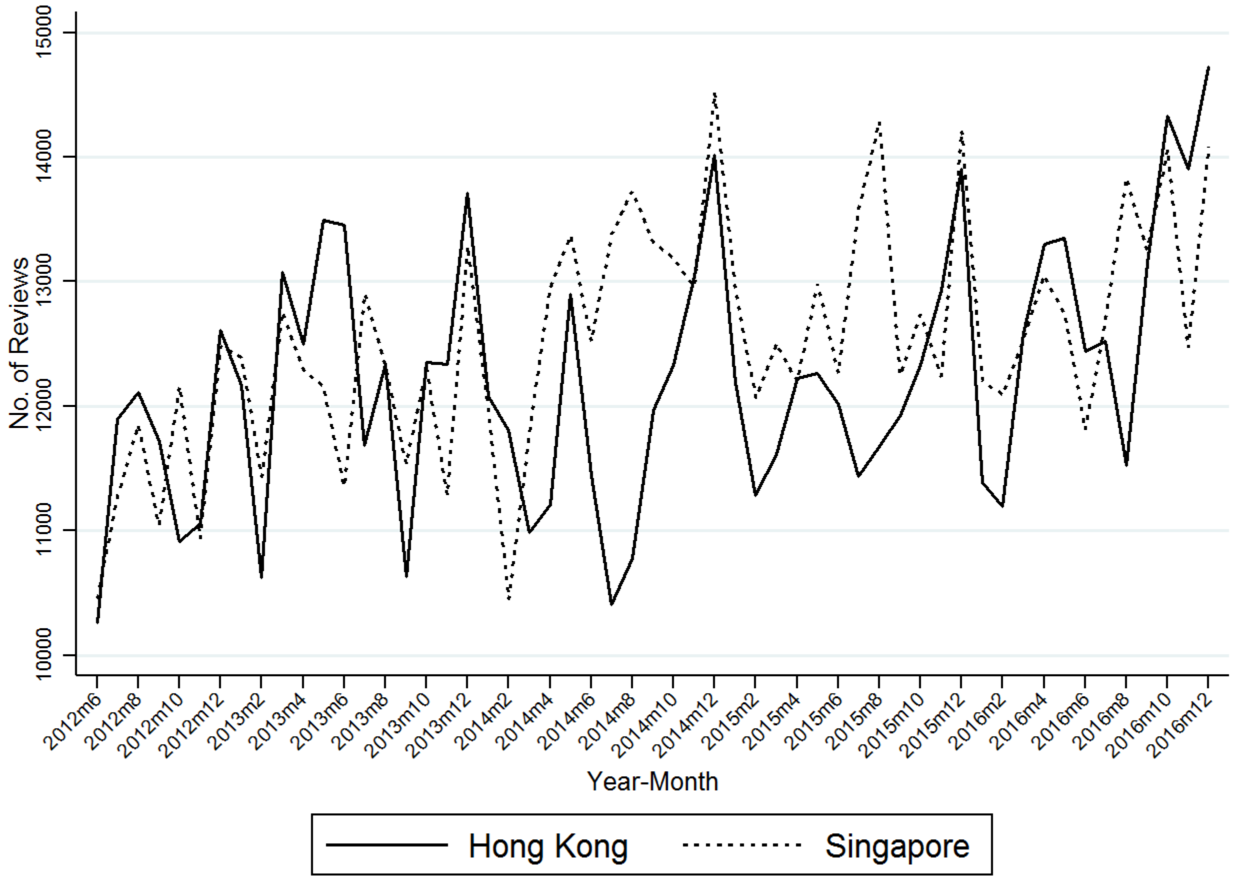
$Post$: is a binary variable that equals 1 if the review is made by a guest for his/her stay after the haze shock in 2013 m6.

$Response_{t-1}$: it has two measures, one is the number of responses, and the other one is the response rate (in percentage).

$no.of sentences$: is the number of sentences in a review.

**Appendix B. Figures and Tables**

Figure B1: The Frequency of Hotel Online Reviews from Jun 2012 to Dec 2016




*Notes*: This figure plots the monthly frequency of online reviews for hotels in Singapore from Jun 2012 to Dec 2016.

Table B2. A Comparison of Hong Kong and Singapore

| **Panel A.** Hotels by Star Rating<br>Number of Hotels (Average Room Rate) | Singapore | Hong Kong |
|---|---|---|
| 5-star | 59 (S$306.7) | 52 (S$400.6) |
| 4-star | 86 (S$159.1) | 164 (S$210.7) |
| 3-star | 99 (S$116.3) | 115 (S$132.0) |
| 2-star | 115 (S$82.1) | 93 (S$59.8) |
| 1-star | 54 (S$55.1) | 109 (S$53.0) |
| Not rated | 32 (S$132.5) | 132 (S$105.6) |
| Total | 445 | 665 |

| **Panel B.** Statistics | Singapore | Hong Kong |
|---|---|---|
| Annual GDP (2016) | 309,754 million$ | 320,881 million$ |
| GDP per capita (2016) | 55,241$ | 43,497$ |
| Service sector as GDP (2016) | 75% | 93% |
| Unemployment rate (2017Q1) | 3.0% | 3.2% |
| Top tax rate (2016) | 22.0% | 15.0% |
| Surface Area (2017) | 709 $km^2$ | 1,050 $km^2$ |
| Population (2017) | 5,607,000 | 7,410,000 |
| % of Chinese (2016) | 77% | 94% |
| Birth Rate (2015) | 9.70 | 8.20 |
| Fertility Rate (2015) | 1.24 | 1.20 |
| Corruption Index (2017) | 84 | 77 |
| $CO_2$ Tons per capita (2015) | 8.66 | 6.27 |
| Period under British Rule | 1819-1959 | 1841-1997 |
| Period under Japanese Occupation | 1942-1945 | 1942-1945 |

*Notes*: This table compares and contrasts Hong Kong and Singapore with known quantitative statistics. Panel A shows the number of hotels and average prices (in bracket) of hotels breakdown by star rating and Panel B compares socioeconomic statistics of two regions.

Table B3. Top 20 Countries of Travellers and Summary of Guest Types in Singapore and Hong Kong

| Singapore | | | | Hong Kong | | | |
|---|---|---|---|---|---|---|---|
| Guest Country | Obs. | Guest Types | Obs. | Guest Country | Obs. | Guest Types | Obs. |
| China | 94,295 | Couple | 183,143 (29.48%) | China | 79,070 | Couple | 152,349 (27.11%) |
| Indonesia | 74,039 | Family | 123,275 (19.84%) | Singapore | 52,312 | Family | 98,809 (17.58%) |
| Australia | 71,758 | Business | 98,769 (15.90%) | Taiwan | 47,322 | Business | 95,343 (16.96%) |
| Malaysia | 60,415 | Solo | 72,991 (11.75%) | United States | 36,434 | Solo | 87,425 (15.55%) |
| Japan | 33,186 | Group | 32,732 (5.27%) | Australia | 36,338 | Group | 34,471 (6.13%) |
| United Kingdom | 33,170 | Friends | 14,591 (2.35%) | Malaysia | 36,022 | Friends | 11,629 (2.07%) |
| Thailand | 30,500 | Other | 95,750 (15.41%) | Japan | 32,578 | Other | 150,391 (14.59%) |
| United States | 26,068 | | | Thailand | 32,182 | | |
| Philippines | 25,570 | | | United Kingdom | 27,519 | | |
| Hong Kong | 24,171 | | | Philippines | 26,592 | | |
| Taiwan | 19,347 | | | South Korea | 25,775 | | |
| South Korea | 17,129 | | | Indonesia | 17,198 | | |
| India | 17,129 | | | Canada | 13,115 | | |
| Vietnam | 10,966 | | | Macau | 10,579 | | |
| Germany | 9,841 | | | India | 8,465 | | |
| New Zealand | 7,597 | | | Russia | 7,648 | | |
| Canada | 6,999 | | | Germany | 6,367 | | |
| France | 6,924 | | | France | 5,839 | | |
| Russia | 5,476 | | | New Zealand | 4,821 | | |
| Italy | 5,240 | | | Italy | 3,613 | | |

*Notes*: This table lists the top 20 countries of origin of travellers who visited Singapore and Hong Kong from June 2012 to December 2016. It also reports the sample distributions by guest type.

Table B4. Responses of Online Review Score to the Haze Shock in June 2013

(Sample Period: from June 2012 to August 2014)

| Haze Measure<br>Model | $Shock^b$<br>(1) | $ln(PSI^{mean})$<br>(2) | $ln(PSI^{max})$<br>(3) | $DoH$<br>(4) | PSI Category<br>(5) |
|---|---|---|---|---|---|
| Haze | -0.431*** | -0.335*** | -0.395*** | -0.032*** | |
| | (0.068) | (0.052) | (0.045) | (0.006) | |
| PSI_{61-120} | | | | | -0.161*** |
| | | | | | (0.033) |
| PSI_{above 120} | | | | | -0.657*** |
| | | | | | (0.090) |
| ln(Temperature) | 0.056*** | 0.105*** | 0.061*** | 0.059*** | 0.123*** |
| | (0.019) | (0.024) | (0.018) | (0.019) | (0.028) |
| ln(Wind) | 0.127*** | 0.097*** | 0.198*** | 0.134*** | 0.143*** |
| | (0.030) | (0.029) | (0.030) | (0.030) | (0.030) |
| ln(Rainfall) | -0.011** | 0.009 | -0.018*** | -0.010* | 0.020** |
| | (0.005) | (0.006) | (0.006) | (0.005) | (0.009) |
| ln(Visibility) | 0.041** | 0.087*** | -0.037 | 0.055*** | -0.019 |
| | (0.020) | (0.017) | (0.027) | (0.021) | (0.025) |
| Constant | 4.646*** | 3.786*** | 6.571*** | 4.438*** | 2.947*** |
| | (0.522) | (0.545) | (0.568) | (0.527) | (0.722) |
| Observations | 313,501 | 313,501 | 313,501 | 313,501 | 313,501 |
| R-squared | 0.208 | 0.208 | 0.208 | 0.208 | 0.208 |
| Year and Month FE | YES | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO | NO |
| Country of Origin FE | YES | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES | YES |

*Notes*: This table presents the regression results of estimating Equation (1) using hotel online review data in Singapore from June 2012 to August 2014. The dependent variable is review score. Five different measures of air pollutants are used in the analysis. $Shock^b$ represents the severe shocks in Jun 2013, $DoH$ measures the number of days per month with haze status, and $PSICategory$ classifies the monthly average $PSI^{max}$ into three categories: 0-60, 61 to 120, and above 120. Year fixed effect, month fixed effect, guests' country of origin fixed effect, website effect, guest type effect, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table B5. DID Estimations: Ex-ante versus Ex-Post Responses of Online Review Scores

(Singapore VS. Hong Kong from June 2012 to August 2014)

| Subcategory<br>Model | Cleanliness<br>(1) | Service<br>(2) | Location<br>(3) | Sleep<br>(4) | Value<br>(5) | Room<br>(6) |
|---|---|---|---|---|---|---|
| $Treatment_c * Pre$ | -0.003 | -0.073 | 0.004 | -0.037 | -0.063 | -0.017 |
| | (0.042) | (0.052) | (0.020) | (0.024) | (0.054) | (0.023) |
| $Treatment_c * Post$ | 0.198*** | 0.250*** | 0.021 | 0.018 | 0.400*** | 0.029 |
| | (0.045) | (0.053) | (0.021) | (0.024) | (0.054) | (0.026) |
| ln(Temperature) | -0.008* | -0.002 | 0.001 | 0.004* | 0.008* | 0.001 |
| | (0.004) | (0.004) | (0.002) | (0.002) | (0.004) | (0.002) |
| ln(Wind) | -0.077** | -0.038 | -0.004 | -0.021 | -0.047 | -0.018 |
| | (0.036) | (0.040) | (0.017) | (0.020) | (0.045) | (0.021) |
| ln(Rainfall) | 0.020*** | 0.017** | -0.003 | 0.003 | 0.008 | 0.003 |
| | (0.006) | (0.007) | (0.003) | (0.003) | (0.007) | (0.003) |
| ln(Visibility) | 0.029 | 0.044 | -0.006 | 0.009 | 0.050 | 0.001 |
| | (0.023) | (0.030) | (0.012) | (0.014) | (0.034) | (0.013) |
| Constant | 8.877*** | 8.001*** | 4.255*** | 4.119*** | 6.991*** | 3.443*** |
| | (0.376) | (0.510) | (0.222) | (0.213) | (0.509) | (0.226) |
| Observations | 85,756 | 93,084 | 85,639 | 80,089 | 85,459 | 85,313 |
| R-squared | 0.212 | 0.184 | 0.252 | 0.203 | 0.122 | 0.271 |
| Year and Month FE | NO | NO | NO | NO | NO | NO |
| Year-Month FE | YES | YES | YES | YES | YES | YES |
| Country of Origin FE | YES | YES | YES | YES | YES | YES |
| Sub-Category FE | YES | YES | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES | YES | YES |

*Notes*: This table shows the ex-ante and ex-post responses of subcategory review scores to air pollution events from June 2012 to August 2014. $Treatment_c$ is a binary variable equal to 1 for online reviews of hotels in Singapore, and is equal to 0 for online reviews of hotels in Hong Kong. $Pre$ is a binary variable equal to 1 for the months before the June 2013 haze shock, and $Post$ is a binary variable equal to 1 for twelve months after the haze shock. The dependent variable is subcategory review score. Year fixed effect, month fixed effect, guests' country of origin fixed effect, website effect, guest type effect, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table B6. Ex-ante versus Ex-Post Responses of Subcategory Review Scores

| Pre- and Post- Period<br>Model | -9m,+12m<br>(1) | -6m,+12m<br>(2) | -3m,+12m<br>(3) |
|---|---|---|---|
| $Treatment_p * Pre$ | 0.043 | -0.013 | 0.006 |
| | (0.029) | (0.030) | (0.026) |
| $Treatment_p * Post$ | 0.279*** | 0.239*** | 0.243*** |
| | (0.042) | (0.037) | (0.032) |
| ln(Temperature) | 0.262 | 0.718 | 0.648 |
| | (0.743) | (0.777) | (0.806) |
| ln(Wind) | 0.042 | 0.010 | -0.022 |
| | (0.057) | (0.058) | (0.068) |
| ln(Rainfall) | -0.010 | -0.007 | -0.011 |
| | (0.008) | (0.008) | (0.011) |
| ln(Visibility) | -0.041 | -0.050 | -0.061 |
| | (0.044) | (0.044) | (0.046) |
| Constant | 8.022*** | 6.644** | 7.080** |
| | (2.511) | (2.583) | (2.751) |
| Observations | 261,787 | 261,787 | 261,787 |
| R-squared | 0.176 | 0.176 | 0.176 |
| Year and Month FE | YES | YES | YES |
| Year-Month FE | NO | NO | NO |
| Country of Origin FE | YES | YES | YES |
| Sub-Catergory FE | YES | YES | YES |
| Guest Type FE | YES | YES | YES |
| Hotel FE | YES | YES | YES |

*Notes*: Panel A studies the difference in the responses of subcategory online review scores (e.g., improvable category and non-improvable category) to the air pollution for hotels in Singapore using the difference-in-differences approach. Panel B utilizes hotel reviews in both Singapore and Hong Kong and compares the haze effects to improvable and non-improvable categories using a triple differences method. Year, month, guests' country of origin, website, guest type, sub-category, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table B7. The Likelihood of Reviewers Leaving Negative Comments during the Haze Episodes

(Subsample from *Expedia*)

| Haze Measure | $Shock^b$ | $ln(PSI^{max})$ | $DoH$ | PSI Category |
|---|---|---|---|---|
| Model | (1) | (2) | (3) | (4) |
| Haze | 0.749*** | 0.270** | 0.004 | |
| | (0.197) | (0.121) | (0.013) | |
| $PSI_{61-120}$ | | | | 0.330*** |
| | | | | (0.054) |
| $PSI_{above120}$ | | | | 0.923*** |
| | | | | (0.197) |
| ln(Temperature) | 0.039 | 0.026 | 0.066** | -0.01 |
| | (0.029) | (0.031) | (0.028) | (0.028) |
| ln(Wind) | -0.062*** | -0.057*** | -0.055*** | -0.079*** |
| | (0.007) | (0.007) | (0.007) | (0.008) |
| ln(Rainfall) | 0.079*** | 0.057*** | 0.069*** | 0.030* |
| | (0.015) | (0.014) | (0.015) | (0.015) |
| ln(Visibility) | 0.261*** | 0.097*** | 0.060 | 0.258*** |
| | (0.063) | (0.028) | (0.067) | (0.064) |
| Constant | -3.420** | -2.352 | -2.407 | -1.346 |
| | (1.433) | (1.442) | (1.480) | (1.439) |
| Observations | 57,908 | 57,908 | 57,908 | 57,908 |
| Pseudo $R^2$ | 0.138 | 0.161 | 0.172 | 0.203 |
| Year and Month FE | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO |
| Country of Origin FE | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES |

*Notes*: This table presents the results showing the likelihood of a traveller to leave a negative comment if he/she stays in the hotel during the haze period. The dependent variable is a binary variable equal to 1 if a reviewer leaves a negative comment, and 0 otherwise. Year, month, guests' country of origin, guest type, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table B8. The Likelihood for Hotel Managers Responding to Online Reviews

(Subsample from *TripAdvisor* and *Expedia*)

| Haze Measure<br>Model | $Shock^b$<br>(1) | $ln(PSI^{max})$<br>(2) | $DoH$<br>(3) | PSI Category<br>(4) |
|---|---|---|---|---|
| Haze | 0.159*** | 0.112*** | 0.009*** | |
| | (0.031) | (0.035) | (0.002) | |
| $PSI_{61-120}$ | | | | -0.011 |
| | | | | (0.018) |
| $PSI_{above120}$ | | | | 0.281*** |
| | | | | (0.041) |
| Review Score | -0.033*** | -0.033*** | -0.033*** | -0.033*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| ln(No. of sentences) | 0.089*** | 0.089*** | 0.088*** | 0.088*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Constant | -0.049 | -0.409 | -0.049 | -0.048 |
| | (1.009) | (1.012) | (1.009) | (1.010) |
| Observations | 227,879 | 227,879 | 227,879 | 227,879 |
| Pseudo $R^2$ | 0.292 | 0.304 | 0.34 | 0.294 |
| Year and Month FE | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO |
| Country of Origin FE | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES |

*Notes*: This table presents the results showing the likelihood for hotel managers to respond to online reviews. the dependent variable is a binary variable equal to 1 if a manager responds to a review rated by individual $i$ for the stay in year-month $t$ at hotel $j$ on website $k$, and 0 otherwise. Year, month, guests' country of origin, guest type, website, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table B9. The Impact of Manager Responses on Online Review Scores

| | Panel A: ln(no. of response) | | | | Panel B: Response Rate (%) | | | |
|---|---|---|---|---|---|---|---|---|
| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Haze Measure | $Shock^a$ | $Shock^b$ | $ln(PSI^{max})$ | $DoH$ | $Shock^a$ | $Shock^b$ | $ln(PSI^{max})$ | $DoH$ |
| $Response_{t-1}$ | 0.061*** | 0.060*** | 0.059*** | 0.059*** | 0.125** | 0.129** | 0.120** | 0.127** |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.061) | (0.061) | (0.061) | (0.061) |
| Haze | -0.389*** | -0.564*** | -0.374*** | -0.070*** | -0.388*** | -0.566*** | -0.373*** | -0.070*** |
| | (0.048) | (0.157) | (0.067) | (0.010) | (0.048) | (0.157) | (0.067) | (0.010) |
| ln(Temperature) | 0.025 | -0.048* | 0.015 | -0.044* | 0.025 | -0.048* | 0.015 | -0.044* |
| | (0.028) | (0.025) | (0.029) | (0.025) | (0.028) | (0.025) | (0.029) | (0.025) |
| ln(Wind) | -0.005 | 0.001 | 0.007 | -0.006 | -0.005 | 0.001 | 0.007 | -0.006 |
| | (0.007) | (0.007) | (0.008) | (0.007) | (0.007) | (0.007) | (0.008) | (0.007) |
| ln(Rainfall) | -0.029** | -0.053*** | -0.031** | -0.058*** | -0.029** | -0.053*** | -0.031** | -0.058*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| ln(Visibility) | 0.099*** | 0.033 | 0.058* | -0.152*** | 0.099*** | 0.032 | 0.057* | -0.152*** |
| | (0.019) | (0.049) | (0.029) | (0.054) | (0.019) | (0.049) | (0.029) | (0.054) |
| Constant | 5.687*** | 8.631*** | 7.650*** | 10.375*** | 5.708*** | 8.647*** | 7.663*** | 10.392*** |
| | (0.869) | (0.899) | (0.834) | (0.932) | (0.870) | (0.899) | (0.835) | (0.932) |
| Observations | 12,744 | 12,744 | 12,744 | 12,744 | 12,744 | 12,744 | 12,744 | 12,744 |
| R-squared | 0.545 | 0.543 | 0.544 | 0.544 | 0.545 | 0.542 | 0.543 | 0.543 |
| Year and Month FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO | NO | NO | NO | NO |
| Country of Origin FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES | YES | YES | YES | YES |

*Notes*: This table studies the impact of managers' responses on hotel review scores in the next period using the following specification (10). The dependent variable is the average online review score for hotel $j$ on website $k$ in year-month $t$. $Response_{j,k,t-1}$ refers to the logarithmic total number of responses (in Panel A) or the response rate in percentage (in Panel B) in the previous period $t-1$. Year, month, website, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table B10. Ex-ante versus Ex-Post Responses of Online Review Scores

| Event | **Jun 2013 Haze** | | **Sep-Oct 2015 Haze** | |
|---|---|---|---|---|
| Post vs. Pre Period | *Period 2 vs. Period 1* | *Period 3 vs. Period 1* | *Period 4 vs. Period 3* | *Period 4 vs. Period 1* |
| Model | (1) | (2) | (3) | (4) |
| Post | 0.226*** | 0.143 | 0.215*** | 0.257*** |
| | (0.030) | (0.140) | (0.033) | (0.038) |
| ln(Temperature) | 0.128*** | -0.143 | 0.092*** | 0.037* |
| | (0.024) | (0.126) | (0.020) | (0.021) |
| ln(Wind) | -0.013*** | -0.004 | -0.010 | -0.004 |
| | (0.005) | (0.014) | (0.007) | (0.004) |
| ln(Rainfall) | 0.015** | -0.040*** | -0.022** | 0.007 |
| | (0.007) | (0.014) | (0.009) | (0.012) |
| ln(Visibility) | 0.009 | 0.323 | -0.173*** | -0.075** |
| | (0.022) | (0.282) | (0.058) | (0.031) |
| Constant | 3.141*** | 8.857*** | 7.323*** | 6.901*** |
| | (0.644) | (1.614) | (0.675) | (0.703) |
| Observations | 299,882 | 236,901 | 251,487 | 286,452 |
| R-squared | 0.220 | 0.224 | 0.214 | 0.218 |
| Year and Month FE | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO |
| Hotel-Month FE | YES | YES | YES | YES |
| Country of Origin FE | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES |

*Notes*: This table provides the estimation for the model specification 2. The coefficients on *Post* show the differences between the online review scores before and after two severe haze shocks. The dependent variable is review score. we divide the sample period into four periods: Jun 2012 to May 2013 (period 1, the pre-shock period of the Jun 2013 haze), Jul 2013 to Aug 2014 (period 2, the post-shock period of the Jun 2013 haze), Dec 2014 to Aug 2015 (period 3, the pre-shock period of the Sep-Oct 2015 haze), and Nov 2015 to Dec 2016 (period 4, the post-shock period of the Sep-Oct 2015 haze). Year, hotel-month, guests' country of origin, website, guest type, and hotel fixed effects are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

Table B11. Quqantile Regressions (QR) for Ex-ante versus Ex-Post Responses of Online Review Scores

| Method | OLS (1) | QR (0.25) (2) | QR (0.5) (3) | QR (0.75) (4) |
|---|---|---|---|---|
| Post | 0.224*** | 0.096*** | 0.312*** | 0.165*** |
| | (0.028) | (0.037) | (0.010) | (0.058) |
| ln(Temperature) | 0.124*** | 0.112*** | 0.181*** | 0.115*** |
| | (0.022) | (0.023) | (0.006) | (0.036) |
| ln(Wind) | -0.008* | -0.034*** | -0.041*** | -0.000 |
| | (0.004) | (0.006) | (0.002) | (0.010) |
| ln(Rainfall) | 0.015** | 0.008 | 0.022*** | 0.063*** |
| | (0.006) | (0.008) | (0.002) | (0.013) |
| ln(Visibility) | 0.014 | -0.040 | -0.011 | 0.227*** |
| | (0.021) | (0.031) | (0.008) | (0.049) |
| Constant | 3.280*** | 3.148*** | 2.870*** | 2.647** |
| | (0.569) | (0.687) | (0.188) | (1.083) |
| Observations | 299,882 | 299,882 | 299,882 | 299,882 |
| R-squared/Pseudo R2 | 0.207 | 0.129 | 0.092 | 0.101 |
| Year and Month FE | YES | YES | YES | YES |
| Year-Month FE | NO | NO | NO | NO |
| Country of Origin FE | YES | YES | YES | YES |
| Website FE | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES |

*Notes*: This table provides the quatile estimations for the model specification 2. The coefficients on *Post* show the differences between the online review scores before and after two severe haze shocks. The dependent variable is review score. The headers in the first row indicate the regression methodology. The sample period is from Jun 2012 to Aug 2014. Year, month, guests' country of origin, website, guest type, and hotel fixed effects are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** $p<0.01$, ** $p<0.05$,* $p<0.1$.

Table B12. Tests Using Only Frequent Travellers

| | | Sub-Category | | | | | |
|---|---|---|---|---|---|---|---|
| Dep. Variables | Total Score | Cleanliness | Service | Value | Sleep | Location | Rooms |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Post | 0.488** | 0.095 | 0.598*** | 0.151** | 0.186 | 0.025 | -0.295 |
| | (0.171) | (0.180) | (0.076) | (0.043) | (0.149) | (0.054) | (0.185) |
| ln(Temperature) | -0.184** | -0.016 | -0.121 | -0.078** | 0.045 | -0.060** | -0.118 |
| | (0.070) | (0.024) | (0.097) | (0.026) | (0.038) | (0.021) | (0.113) |
| ln(Wind) | 0.040 | -0.041 | 0.043** | 0.024 | -0.037*** | -0.022 | 0.001 |
| | (0.025) | (0.030) | (0.011) | (0.015) | (0.003) | (0.016) | (0.015) |
| ln(Rainfall) | -0.045* | -0.016 | -0.053* | -0.059 | -0.047** | -0.063* | -0.065 |
| | (0.019) | (0.020) | (0.025) | (0.031) | (0.013) | (0.025) | (0.072) |
| ln(Visibility) | 0.011 | -0.211** | -0.007 | 0.104 | -0.092** | -0.130** | 0.064 |
| | (0.037) | (0.081) | (0.064) | (0.144) | (0.033) | (0.035) | (0.156) |
| Constant | 13.140*** | 10.974*** | 10.858** | 7.866** | 8.100*** | 12.152*** | 11.081* |
| | (2.663) | (0.557) | (3.600) | (2.535) | (1.654) | (1.113) | (5.080) |
| Observations | 6,218 | 5,299 | 5,699 | 5,246 | 5,198 | 5,242 | 5,255 |
| R-squared | 0.140 | 0.103 | 0.156 | 0.136 | 0.124 | 0.109 | 0.123 |
| Year and Month FE | YES | YES | YES | YES | YES | YES | YES |
| Country of Origin FE | YES | YES | YES | YES | YES | YES | YES |
| Guest Type FE | YES | YES | YES | YES | YES | YES | YES |
| Hotel FE | YES | YES | YES | YES | YES | YES | YES |

*Notes*: This table provides the estimation for the model specification 2 using frequent travellers only. The coefficients on *Post* show the differences between the online review scores before and after two severe haze shocks. The dependent variable in Column (1) is the total review score and the dependent variables in Columns (2)-(7) are sub category review scores. We use the sample period between Jun 2012 and May 2013 (period 1, the pre-shock period of the Jun 2013 haze) for regressions. Year, month, guests' country of origin, website, guest type, and hotel fixed effects are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

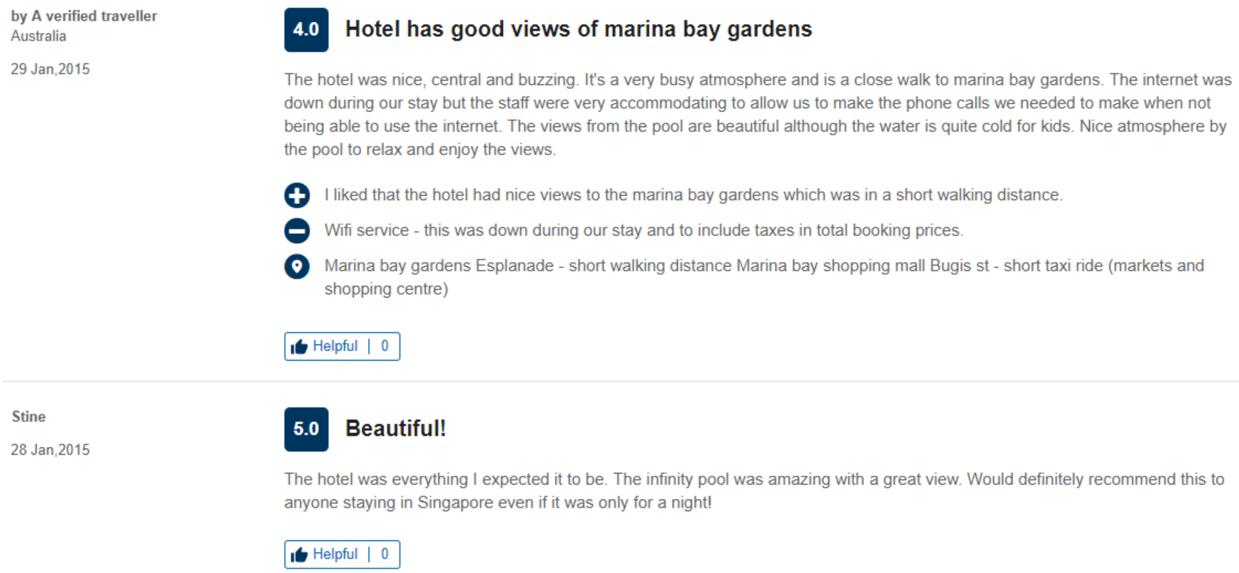
Table B13. Falsification Tests

| Shock Period<br>Model | Sep 2012<br>(1) | Dec 2012<br>(2) | Mar 2013<br>(3) |
|---|---|---|---|
| $Treatment_c * Treatment_p * Pre$ | -0.041 | -0.038 | -0.053 |
| | (0.084) | (0.071) | (0.065) |
| $Treatment_c * Treatment_p * Post$ | -0.064 | -0.074 | -0.073 |
| | (0.062) | (0.062) | (0.066) |
| $Treatment_c * Pre$ | -0.078 | 0.053 | 0.036 |
| | (0.054) | (0.056) | (0.059) |
| $Treatment_c * Post$ | 0.094 | 0.047 | 0.071 |
| | (0.063) | (0.066) | (0.059) |
| $Treatment_p * Pre$ | -0.013 | 0.034 | 0.034 |
| | (0.042) | (0.042) | (0.042) |
| $Treatment_p * Post$ | 0.017 | 0.044 | 0.051 |
| | (0.041) | (0.042) | (0.041) |
| Constant | 7.007*** | 6.277*** | 6.554*** |
| | (0.551) | (0.559) | (0.509) |
| | | | |
| Observations | 191,178 | 191,178 | 191,178 |
| R-squared | 0.689 | 0.688 | 0.688 |
| Control for Weather | YES | YES | YES |
| Year and Month FE | NO | NO | NO |
| Year-Month FE | YES | YES | YES |
| Country of Origin FE | YES | YES | YES |
| Sub-Category FE | YES | YES | YES |
| Guest Type FE | YES | YES | YES |
| Hotel FE | YES | YES | YES |

*Notes*: This table reports the results of falsification tests using the triple differences Equation (7). The sample period is from June 2012 to June 2013. The headers in the first row indicate the re-assigned shock period before the June 2013 shock episode. Weather control variables, year-month, guests' country of origin, website, guest type, sub-category, and hotel fixed effect are included in all regressions. Robust standard errors are clustered at the hotel level and significance levels are indicated by *** p<0.01, ** p<0.05,* p<0.1.

# Appendix C. Sample Online Review

Figure C1. Sample Online Review on Expedia.com



by A verified traveller
Australia

29 Jan,2015

**4.0** **Hotel has good views of marina bay gardens**

The hotel was nice, central and buzzing. It's a very busy atmosphere and is a close walk to marina bay gardens. The internet was down during our stay but the staff were very accommodating to allow us to make the phone calls we needed to make when not being able to use the internet. The views from the pool are beautiful although the water is quite cold for kids. Nice atmosphere by the pool to relax and enjoy the views.

I liked that the hotel had nice views to the marina bay gardens which was in a short walking distance.

Wifi service - this was down during our stay and to include taxes in total booking prices.

Marina bay gardens Esplanade - short walking distance Marina bay shopping mall Bugis st - short taxi ride (markets and shopping centre)

Helpful | 0

Stine

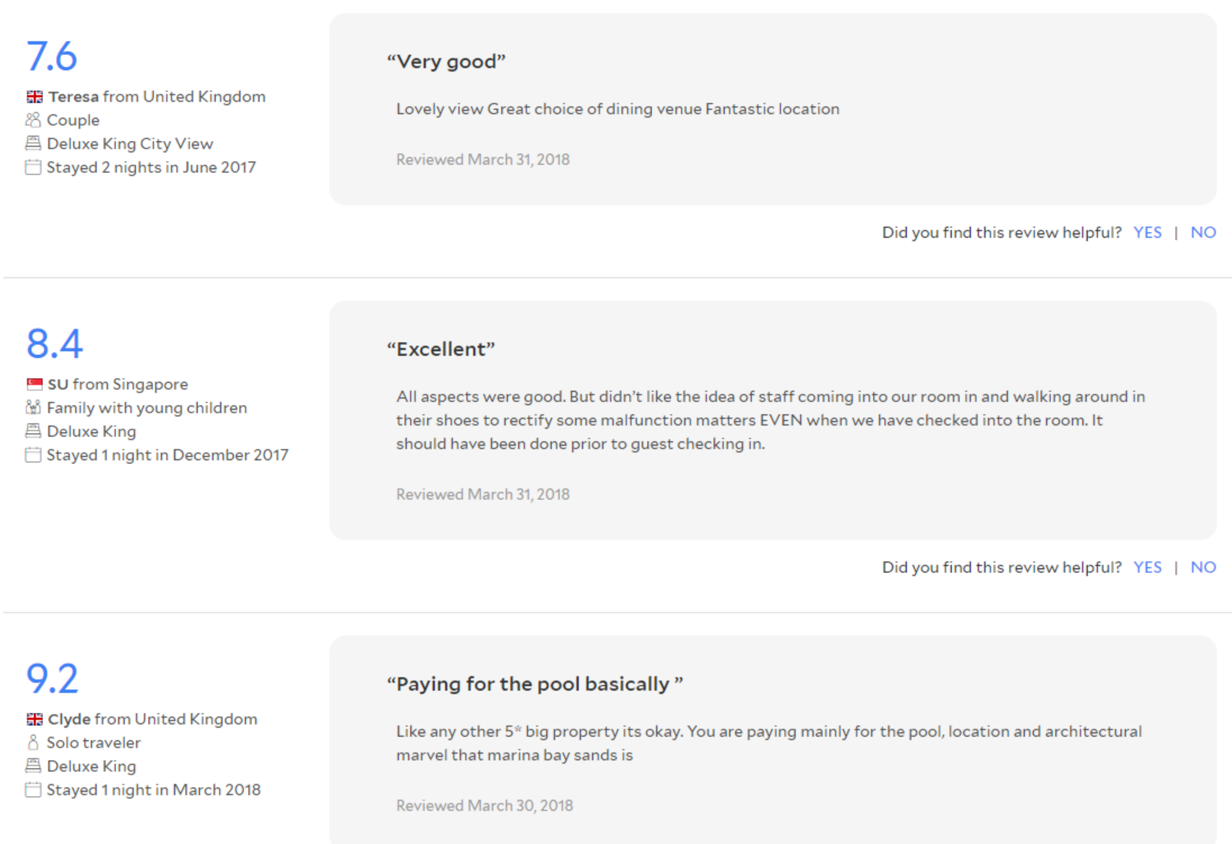
28 Jan,2015

**5.0** **Beautiful!**

The hotel was everything I expected it to be. The infinity pool was amazing with a great view. Would definitely recommend this to anyone staying in Singapore even if it was only for a night!

Helpful | 0

Figure C2. Sample Online Review on Agoda.com



7.6
**Teresa** from United Kingdom
Couple
Deluxe King City View
Stayed 2 nights in June 2017

**"Very good"**

Lovely view Great choice of dining venue Fantastic location

Reviewed March 31, 2018

Did you find this review helpful? YES | NO

8.4
**SU** from Singapore
Family with young children
Deluxe King
Stayed 1 night in December 2017

**"Excellent"**

All aspects were good. But didn't like the idea of staff coming into our room in and walking around in their shoes to rectify some malfunction matters EVEN when we have checked into the room. It should have been done prior to guest checking in.

Reviewed March 31, 2018

Did you find this review helpful? YES | NO

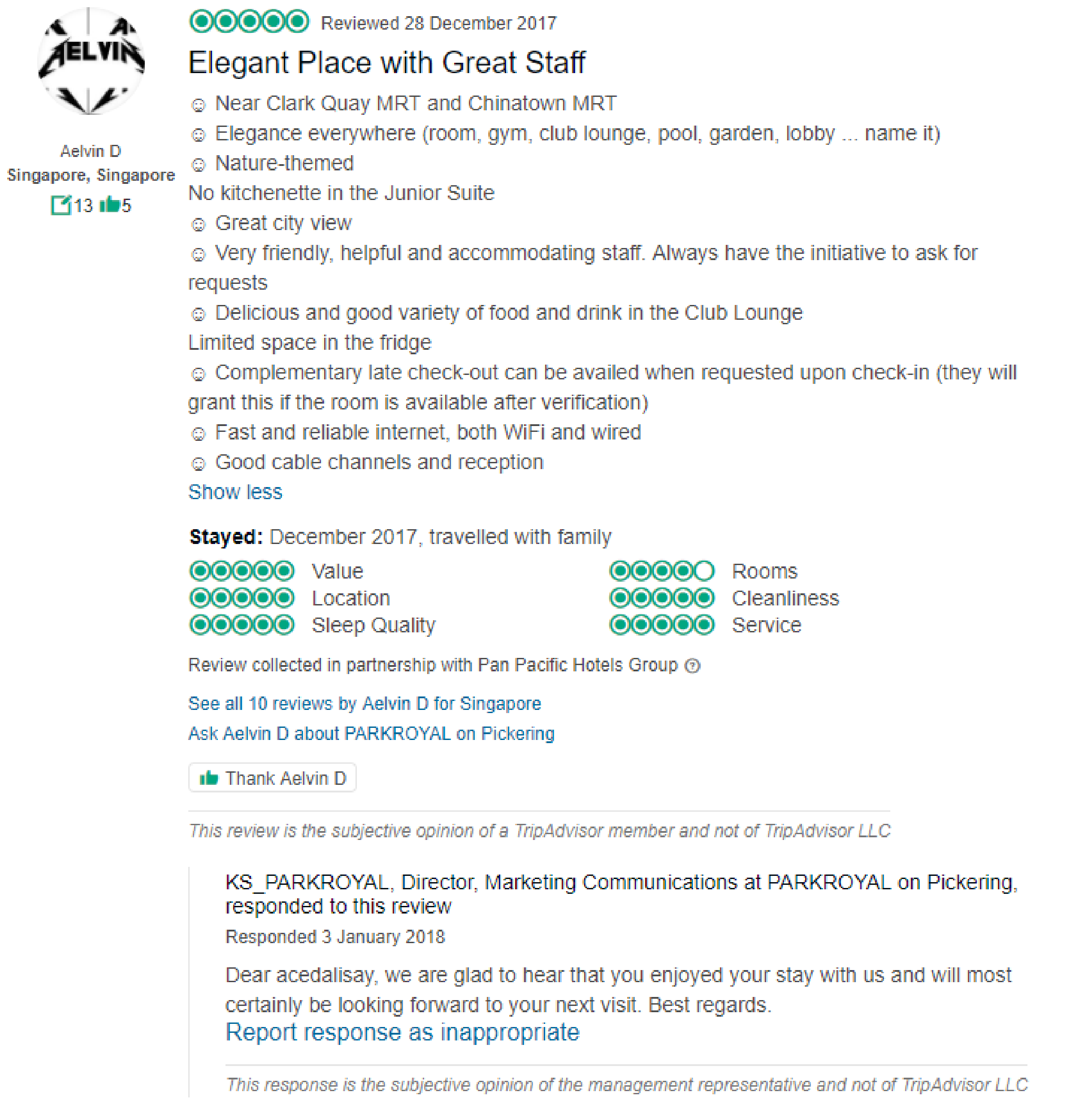
9.2
**Clyde** from United Kingdom
Solo traveler
Deluxe King
Stayed 1 night in March 2018

**"Paying for the pool basically "**

Like any other 5* big property its okay. You are paying mainly for the pool, location and architectural marvel that marina bay sands is

Reviewed March 30, 2018

Figure C3. Sample Online Review on TripAdvisor.com



Aelvin D
Singapore, Singapore
13 5

Reviewed 28 December 2017

Elegant Place with Great Staff

☺ Near Clark Quay MRT and Chinatown MRT
☺ Elegance everywhere (room, gym, club lounge, pool, garden, lobby ... name it)
☺ Nature-themed
No kitchenette in the Junior Suite
☺ Great city view
☺ Very friendly, helpful and accommodating staff. Always have the initiative to ask for requests
☺ Delicious and good variety of food and drink in the Club Lounge
Limited space in the fridge
☺ Complementary late check-out can be availed when requested upon check-in (they will grant this if the room is available after verification)
☺ Fast and reliable internet, both WiFi and wired
☺ Good cable channels and reception
Show less

**Stayed:** December 2017, travelled with family

| | |
|---|---|
| Value | Rooms |
| Location | Cleanliness |
| Sleep Quality | Service |

Review collected in partnership with Pan Pacific Hotels Group

See all 10 reviews by Aelvin D for Singapore
Ask Aelvin D about PARKROYAL on Pickering

Thank Aelvin D

*This review is the subjective opinion of a TripAdvisor member and not of TripAdvisor LLC*

KS_PARKROYAL, Director, Marketing Communications at PARKROYAL on Pickering, responded to this review
Responded 3 January 2018

Dear acedalisay, we are glad to hear that you enjoyed your stay with us and will most certainly be looking forward to your next visit. Best regards.
Report response as inappropriate

*This response is the subjective opinion of the management representative and not of TripAdvisor LLC*