Risk-Avoidance and Environmental Hazard: Effects of Transboundary Haze Pollution in Singapore

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This version: August 31, 2017

Abstract

This paper examines the risk-avoidance behaviors of households in response to environmental hazards using the transboundary haze caused by forest fires in Indonesia as an exogenous shock. Using a unique panel dataset of hourly water consumption at the household level, monthly electricity consumption at the building level, and daily hotel performance indices obtained from multiple sources, this study finds significant positive responses in household utilities consumptions and economic losses in the hotel industry when transboundary haze occurs in Singapore. This study offers three key findings. First, we find evidence from the within-the-day variations and between the weekday to weekend variations in household water consumption that confirms the risk-avoidance responses of households during haze periods. People stay indoors to minimize their exposure to the possible health risks caused by the haze pollutants. These findings are robust to numerous specification checks as well as to when the perceived risk measures obtained from social media are used. Second, we find the long-term persistence of household responses via the high electricity consumption during the two-month haze period; however, electricity consumption responses revert to normal after the haze dissipates. Third, the hotel industry suffers significant losses during the haze period, which is evidence that could suggest the risk-avoidance of foreign visitors, who are informed of the transboundary haze alerts.

Keywords: *Transboundary air pollution, haze, environmental externalities, risk-avoidance economic activities, household utilities*

JEL Code: D12, F62, Q53, Q54

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We would like to thank the National Environmental Agency (NEA) and Public Utilities Board (PUB) for sharing the electricity consumption and water data used in this study. We would also like to thank Daniel McMillen, Tsur Somerville, Yuming Fu and participants in the "Asian Green Cities" Workshop in Tsinghua University, Beijing, China, for their valuable comments and suggestions.

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1. Introduction

Open burning performed by irresponsible companies to clear forests for agricultural purposes has been a main cause of the massive wildfires seen in some countries. However, while the burning-related air pollution is mostly caused by local sources of emissions, containing pollutants generated by forest fires, such as dust, haze, smoke, and toxic gases, within the source region is difficult. The prevailing winds can blow the airborne pollutants to faraway areas, giving rise to transboundary air pollution.

The recent episodes of forest fires in Indonesia in October 2015 generated intense haze that shrouded not only the skies of Indonesia but also those of its closest neighbors, Singapore and Malaysia. Based on the sources cited by the Wall Street Journal,[1] the Indonesian government alone incurred an estimated US$14 billion in haze-related economic losses, environmental damage, health expenses, and business losses.[2] Moreover, Singapore is periodically affected by severe smoke haze from forest fires in the neighboring Indonesia. The haze crisis not only had adverse economic consequences for the Indonesian economy but also caused significant negative external consequences in its neighboring countries. The high concentrations of pollutants, especially that of the suspended particulate matter (PM), increase respiratory-related illnesses, while the poor visibility of haze-clouded skies can cause the grounding of flights. Further, the Ministry of Education of Singapore closed schools and rescheduled school examinations as mitigating measures to prevent haze-related health risks.[3]

While prior research has mainly focused on the issues of air pollution in the US, limited studies have been conducted in other countries, especially in Southeast Asia, where the air pollution caused by forest fires has become rampant in recent years (Jayachandran, 2009; Rosales and Triyana, 2016). This paper extends the existing literature by addressing the issue of transboundary air pollution in Southeast Asia. Our study uses the haze crises of Indonesia as random exogenous shocks to set up a natural experiment to assess the direct impact of air pollution on the daily activities of local households. We use a unique dataset of household utilities consumption to rigorously test the environmental externalities and the risk-avoidance behavior of urban dwellers.

The major challenge facing many studies on urban environmental risks is finding ways to disentangle the endogenous relationships between air pollution and human activities. The two events are highly correlated with coincident weather conditions, seasonal trends, and local economic activities.[4] Instruments including the boat arrivals at the Port of Los Angeles (Moretti and Neidell, 2011) and the Clean Air Act Amendments (Greenstone, 2002; Chay and Greenstone,

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1 A press release was issued on September 24, 2015 by the MOE of Singapore to close kindergartens, primary, secondary and special education schools on September 25, 2015.

2 Source: "The numbers: Indonesia's Haze", the Wall Street Journal, October 27, 2015.

3 Another unofficial source estimated the costs associated with Indonesia's haze events to be as high as US$47 billion. (Source: Francis Chan, "$47b? Indonesia counts costs of haze", The Straits Times, October 11, 2015.)

4 Graff Zivin and Neidell (2013) provide a comprehensive review of the environmental risk impacts on human health, and Deschenes (2012) reviews the literature that relates human health outcomes to temperature and temperature extreme adaptions.

2003; Bento, Freedman, and Lang, 2015) have been used in environment-related studies to simulate exogenous shocks. The transboundary haze events in Indonesia, which are likely to generate unanticipated negative and immediate reversal effects on human activities, are used as exogenous shocks in our natural experimental study.[5] The exogenous haze shocks generated by forest fires in Indonesia are captured by the 24-hour Pollutant Standard Index (PSI). The National Environment Agency (NEA) in Singapore provides the 24-hour PSI readings, an hourly measure over a rolling 24-hour period, between January 1, 2012 and December 31, 2015. The fluctuations are independent of local economic activities and seasonal changes, but are correlated with the forest fires in neighboring Indonesia. To control for other weather confounders, we also collect weather data from The Weather Company (on an hourly interval) and Meteorological Service Singapore (on a monthly interval).

Our empirical strategy exploits the random and high-frequency fluctuations in ambient air quality during the haze periods and tests whether the haze shocks significantly influence daily human activities and risk-avoidance behavior. We merge several unique datasets, which include two datasets on household utility consumption (at an hourly and monthly frequency) and one on the daily hotel performance in Singapore, to characterize the relationships between air pollution and human activities.

There are three key findings from our analyses. First, based on a unique dataset provided by the Singapore Public Utilities Board (PUB), which contains detailed information of the hourly water consumption of 376 households from January 1, 2012 to December 31, 2014, we find that a 100% increase in the hourly 24-hour PSI reading is associated with an average water consumption increase of 5.1%. Based on the evidence from the same-day (daytime versus nighttime effects) and same-week variations (weekday versus weekend effects) of household water consumption, we also find that haze events increase water consumption significantly on weekday nights and weekends. The results support not only the positive haze effects on water consumption but also, more importantly, the positive responses of weekday-night and weekend-day water consumption, implying that households have reduced their exposure to air-pollution risks by staying indoors during weekday nights and weekend days. The results support the presence of risk-avoidance behaviors of households and remain robust after controlling for various confounders, such as "bad" weather conditions and peak-hour and off-peak-hour consumptions. In our heterogeneity tests, we find that water-consumption responses vary with race, such that Malay households show stronger consumption responses relative to those of Chinese and Indian households. We also use detailed data from a social media website (Twitter) to study the emotional and sentiment responses[6] of households during the haze periods and their effects on household utility consumption. Our findings affirm that the negative sentiment related to haze could significantly predict increases in water consumption.

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5 A temporary and exogenous shock is similar to the mechanisms widely used in behavioral experiments. For example, using the two-week shutdown of the US Federal Government in 2013 to examine a temporary and exogenous liquidity shock in a difference-in-differences setup, Gelman et al. (2016) studied the consumption responses of affected employees and found that most households have mechanisms to smooth consumption to cope with income and liquidity shocks.

6 Bayer et al. (2009) and Smith and Huang (1995) argue that an individual's behavior is dependent on perceived risk, rather than objective risk. Perceived risk considers the emotions and sentiments of an individual easily influenced by information on social media, such as Twitter.

The second finding presents a longer period (monthly) of household responses to haze and their effects on electricity usage. Based on the monthly electricity data for all the public and private residential buildings (based on 15,315 unique postal codes[7]) in Singapore for the period of January 2013 to December 2015, as collected from the Energy Market Authority (EMA), our analysis reveals a statistically significant positive impact of the monthly average 24-hour PSI readings on household electricity consumption. A 100% increase in the monthly average 24-hour PSI readings is associated with an average electricity consumption increase of 2.34%. Our dynamic analysis of the long-term air-pollution effects shows significantly longer persistence of electricity consumption behavior than water-consumption behavior. While the households revert back to their original water-consumption behaviors one week after experiencing a short-term haze shock, the long-term haze episodes, which last for two months, impact the household electricity consumption habits, causing electricity consumption levels to continue rising over the two months following the long-term shocks.

Third, we use the daily data of the hotel room prices and occupancy rates from a large sample of hotels in Singapore from the hotel data company Smith Travel Research (STR) as proxies of economic outcomes. We show that when the one-day-lagged and daily averages of the 24-hour PSI readings double, the average daily hotel room rates decline by 1.99% and 1.54%, respectively, across the hotels by class segment. Moreover, the haze outbreaks significantly influence hotel room demand. In particular, we find that the haze measurements do not affect the hotel occupancy levels of the same day due to the cancellation penalty that is in place at most hotels. However, hotel demand is significantly affected by the lagged haze measures, such that the coefficients remain economically and statistically significant for up to a six-day lag. The results imply that the risk-avoidance behavior is not only observed by local residents but also by foreigners, who avoid visits to Singapore during the haze periods to lower their haze-related health risks.

This study presents the estimated economic costs associated with the transboundary haze in Singapore. Following the traditional manner of assessing environmental externalities and providing a lower bound of the estimated costs of these environmental externalities (Bento, Freedman, and Lang, 2015; Currie et al., 2015; Chang, Zivin, Gross, and Neidell, 2016), the back-of-the-envelope estimations show that when a heavy-haze shock occurs (the 24-hour PSI reading increases from 60 to 300 and persists for one month, similar to the haze event in 2015), Singaporean household water spending increases by \$12.99 million, and electricity spending increases by \$11.67 million, while the revenues of Singapore's hoteliers decrease by \$5.20 million. This study demonstrates important policy implications for the governments related to the importance of international collaborations in the prevention and mitigation of forest fires and haze.

Moreover, this paper makes three contributions to environmental and air-pollution literature. First, this is the first attempt to find significant evidence of the transboundary air-pollution effects on daily human activities in Southeast Asia. Unlike the earlier studies that use local or regional sources of pollution emissions as exogenous shocks, the haze used in our natural experiment was emitted by Indonesian forest fires and traveled across the country's border to cloud Singapore's skies, creating a clean and exogenous instrument (shock). We do not need to explicitly control for the confounding effects associated with local economic activities (Moretti and Neidell, 2011) or sorting by residents (Chay and Greenstone, 2003a, 2003b, 2005) and firms (Greenstone, 2002).

[7] In Singapore, every building is given a unique postal code.

Furthermore, the tropical climates of Singapore and Indonesia reduce the effects of extreme seasonal and intraday temperature variations that may affect the causal effects of the transboundary haze in Indonesia on human daily activities during the tests.

Second, we present new evidence of humans' risk-avoidance behavior in response to the transboundary haze pollution using within-the-day (daytime and nighttime) and between-the-day (weekday and weekend) variations of their utilities consumption. When the haze level, as indicated by the 24-hour PSI readings, reaches an unhealthy range, we observe avoidance and mitigation behaviors. People reduce their exposure to haze risks by staying at home more after working on weekdays, by avoiding outdoor family outings on weekends when haze readings reach alarming levels, and by consuming more water and electricity after outdoor activities when following government advisories. The evidence of the household risk-avoidance and mitigation behaviors is intuitively and consistently reflected in the household water consumptions, which are significantly higher on weekday nights and weekend days. The same evidence is also found in the monthly electricity consumptions during haze periods. We find that households continue to increase their electricity consumption for as long as two months after the haze clears. Third, the transboundary haze has caused significant economic loss for Singapore's hoteliers. The risk-avoidance behaviors of foreign visitors are reflected by the significant declines in the daily room prices and occupancy rates, as foreign visitors are more likely to stay away from haze-shrouded skies in Singapore.

The remainder of this paper is as follows. Section 2 reviews the related empirical literature. Section 3 provides some background on the transboundary haze that occurs in Singapore and the actions taken by the government to mitigate the health risks of the city's residents. Section 4 describes the data sources and descriptive statistics. Section 5 discusses our identification strategy, econometric methodology, and testable hypotheses for the risk-avoidance behavior. Section 6 presents the main empirical results, which include those from the heterogeneous, robustness, and falsification tests. Section 7 presents the empirical results using the monthly electricity consumption and daily hotel performance indices as alternate outcomes; a general estimation of the welfare costs associated with the transboundary air pollution is also included. Finally, Section 9 concludes the study.

2. Past Studies of Environmental Risks and Avoidance Behaviors

Air pollution and its impacts on climate change have become major global concerns. The literature has increasingly linked air pollution to many of the catastrophic events of recent times. Rosales and Triyana (2016) show that the massive forest fires in Indonesia in 1997 had persistent and negative health impacts on Indonesian children residing in both urban and rural areas and that the children in urban areas with better access to health care services were equally vulnerable to pollution from forest fires. Studies in the US have shown alarming evidence of the negative impacts of air pollution on infant health. Chay and Greenstone (2003) show that approximately 1,300 fewer infants died in 1972 than would have without the Clean Air Act Amendments of 1970. This work also shows that the 1% decline in the total PMs could have resulted in a 0.5% decline of the infant mortality rate between 1970 and 1972; a lower figure of a 0.35% decline of the infant mortality rate was estimated by a separate study from Chay and Greenstone (2003) for between 1980 and 1982. In addition to the effects of a reduction of PMs, reductions of other pollutants, such as carbon monoxide (CO) (Currie and Neidell, 2005) and nitrogen oxide (NO_x) (Deschenes, Greenstone, and Shapiro, 2012), could also reduce the mortality rate.[8] The study of environmental risks and human health outcomes has predominantly been found in health science literature. Many health science studies on the effects of PMs have shown that the absorption of certain chemicals can increase pulmonary cancer and hyperactivity in children (Coffin and Stokinger, 1977; Goldsmith and Friberg, 1977). Poor air conditions have also been found to increase the health risks of other wildlife species over the past two decades (Goldsmith and Friberg, 1977; Patz, 2002; Bell et al., 2011; De Sario et al., 2013).

While a large body of literature links air pollution to poor health outcomes (Goldsmith and Friberg, 1977; Dockery et al., 1993; Friemand et al., 2001; Patz, 2002; Pope et al., 2002; Chay and Greenstone, 2003a, 2003b; Bell et al., 2004; Currie and Neidell, 2005; Moretti and Neidell, 2011; De Sario et al., 2013), the empirical evidence of human behavioral responses to air-pollution risks is still relatively scattered, partially due to the scarcity of microdata and the difficulty of finding natural experimental settings that allow for the identification of the endogenous effects of air pollution on human activities.

Indoor air quality is considerably better than outdoor air quality, allowing the reduction of human exposure to air-pollution risks (Chang et al., 2000). The exposure to pollution is endogenous, and individuals can respond to ambient pollution levels by reducing their time spent outdoors (Neidell, 2009). This avoidance behavior is particularly common among individuals who are susceptible to air pollution (Janke, 2014). Some empirical studies have found evidence of the risk-avoidance behaviors of individuals who take various preemptive steps to minimize their exposure to environmental risks by staying indoors (Graff Zivin and Neidell, 2009; Neidell, 2009). Some individuals change consumption preferences, such as reducing canned fish consumption (Shimshack, Ward, and Beatty, 2007) and drinking bottled water (Graff Zivin, Neidell, and Schlenker, 2011) in response to environmental risk alerts.

Neidell (2009) showed that information on environmental risks, such as smog alerts, could have significant and negative impacts on the attendance rates of two major outdoor facilities in Southern California: the Los Angeles Zoo and Griffith Park Observatory. The results imply that individuals take preemptive steps to reduce their exposure to health risks, and risk-avoidance behavior is a source of endogenous bias, which, if not properly accounted for, can lead to the overestimation of the health impacts of air pollution. The risk-avoidance behavior was also found by Agarwal, Rengarajan, Sing, and Vollmer (2016) in their empirical tests of the effects of noise pollution from construction activities on residential electricity consumption in Singapore. They show that the electricity consumption of households living close to the construction sites increased by 6% compared to those who were not affected by the construction activities.

Recent studies have provided new economic evidence of the effects of exogenous air pollution on labor productivity in the agricultural, industrial, and service sectors, suggesting that air-pollution controls generate a sizable fraction of total welfare benefits (Evans and Jacobs, 1981; Greenstone, 2002; Deschenes and Greenstone, 2011; Deschenes, Greenston, and Shapiro, 2012; Graff Zivin

[8] Currie and Neidell (2005) estimated that the reduction in CO that occurred during the 1990s saved approximately 1,000 infant lives in California. Deschenes, Greenstone, and Shapiro (2012) show that the imposition of a NOx emission cap through the NOx Budget Trading Program could reduce the summer mortality rate in the US by 0.5%, or about 2,200 fewer premature deaths per summer, mainly among individuals aged 75 and older.

and Neidell, 2012; Bento, Freedmand, and Lang, 2015; Chang, Graff Zivin, Gross, and Neidell, 2016; Heyes, Saberian, and Neidell, 2016). Using data of the productivity of agricultural workers, Graff Zivin and Neidell (2012) showed that a 10-parts-per-billion drop in ozone concentration results in a significant 5.5% increase in the productivity of agricultural workers. Chang, Graff Zivin, Gross, and Neidell (2016), however, showed that outdoor air pollution could penetrate indoors and influence the productivity of indoor workers in a pear-packing factory in Northern California. The study showed that an increase of 10 micrograms per cubic meter ($\mu g/m^3$) in $PM_{2.5}$ could reduce labor productivity, which is estimated to be approximately 6% of the average hourly earnings. This negative relationship is reversed when the $PM_{2.5}$ threshold exceeds 15 $\mu g/m^3$. Heyes, Saberian, and Neidell (2016) extended this research to highly skilled workers and showed a negative link between six-day $PM_{2.5}$ variations and S&P500 movements.

The topics of air pollution and its detrimental effects on physical and mental health, the ecosystem, and labor productivity have started to attract attention in economic literature in recent years. Graff Zivin and Neidell (2013) provide a comprehensive review of the economic inquiries into the subject, organizing the studies neatly into three themes: contamination, exposure, and dose-response. Contamination refers to emission sources[9] and transmission mediums, which are important in empirical designs because the concentration and deposition patterns of the selected air pollutions help to identify the causality between pollution and health outcomes. Humans naturally respond to environmental risk information by reducing their exposure to the risk. This risk-avoidance behavior, if unaccounted for, could create a biased estimation of the environmental impact. The non-linear dose-response effects cause a discontinuity in human responses to environmental risks. Controlling for the confounders from local economic activities and other environmental variables is therefore essential to avoid spurious outcomes. Deschenes (2012) also provides another comprehensive survey of the literature covering the issues of health outcomes, temperature variations, and adaptions to extreme temperature.

There are two significant gaps in the literature that this study aims to fill. First, while previous research invariably focuses on the economic and physical health aspects of human behavior in the presence of air pollution, few studies correlate ambient pollutant fluctuations with daily activities and risk-avoidance using data of household utility consumptions. We use a unique set of utility consumption data to show evidence of the risk-avoidance behavior of households in response to air-pollution risks. Households choose to stay indoors to avoid exposure to high concentrations of PMs in polluted outdoor air environments. Second, our study finds a randomized and exogenous shock of air pollution and controls for other confounders, such as weather conditions and seasonal temperature, which have been a challenge for previous studies. While some past studies use policy changes, such as the Clean Air Act Amendments in the US (Greenstone, 2002; Chay and Greenstone, 2003; Bento, Freedman, and Lang, 2015), others use temporal variations in the levels of different pollutants, such as total suspected particulates (TSPs) (Chay and Greenstone, 2003), ozone (O_3) (Currie and Neidell, 2005; Graff Zivin and Neidell, 2012; Chang, Graff Zivin, Gross, and Neidell, 2016), NOx (Deschenes, Greenstone, and Shapiro, 2012), and the year-to-year changes in temperature (Deschenes and Greenstone, 2011; Deschenes, 2012), to set up exogenous shocks to test for the environmental effects on human health outcomes and activities.

[9] Moretti and Neidell (2011) show that boats from countries with less stringent environmental regulations contribute over 20% of the NOx emissions in the Los Angeles area when they arrive in the port of Los Angeles.

We use the transboundary haze in Singapore caused by the forest fires in Indonesia as the exogenous shock in our natural experimental design. In Singapore, most of the polluted oil refineries and petrochemicals are confined to Jurong Island, a reclaimed island to the west of the main island. A set of stringent industrial emission standards and guidelines has also been strictly enforced by the government via its industry agency, the JTC Corporation. Moreover, generous provisions for green buffers have been provided by the government's urban planning authority, the Urban Redevelopment Authority (URA), as part of its "*city in the garden*" planning vision. These are among the policies that have been put in place by the government to create a sustainable living environment, which is clear of industrial pollution. Therefore, Singapore offers an ideal environment to identify the clear effects of air pollution in our natural experiment. After all, the transboundary haze shock is random and exogenous as the shock is purely caused by the forest fires on the neighboring Indonesian islands. The high concentration of $PM_{2.5}$ pollutants in Singapore's skies is independent of the local industries activities.

3. Background of Forest Fires in Indonesia and Haze Alerts in Singapore

It has been common practice for many years for farmers and agricultural landowners in Southeast Asia to use open burning as a cheap, but illegal, way of clearing forestlands for agricultural uses, such as for oil palm plantations. In Indonesia, some peatlands, which are waterlogged lands filled with decomposing forest debris, decaying organisms, and vegetation, have been drained and cleared for oil palm plantations as well as other uses. Drained peatlands are highly susceptible to fires, and when such fires occur, they are difficult to extinguish, especially during the dry El Niño seasons. The smoldering fires occur not just on the surface of peatlands, but permeate up to three meters underneath them.[10] Aerial water bombing from planes, which is widely used to extinguish surface flames, is less effective in peatland fires that occur deep beneath the surface. The smoldering peatland fires can quickly spread to a large area, and the fires underneath the ground can resurface and flare up after a short time, causing extended periods of haze that persist for days or weeks.

The combustion of carbon-rich matter in peatlands and the burning of matured trees in monsoon forests produce plenty of toxic pollutants, such as $PM_{2.5}$, CO, and sulfur dioxide. The toxic gases emitted as well as the ashes, dust, and smoke result in the climate phenomenon commonly referred to as haze. Containing haze within the source locations is difficult. Pollutants, smoke, and dust in the haze could be easily transmitted via prevailing winds that transverse the geographical boundaries of neighboring countries. The haze causes irritation to eyes and when inhaled for a prolonged period of time, can have harmful and damaging long-term effects on the lung and respiratory systems of humans.

In recent years, recurring peatland and forest fires have been the main causes of haze problems, which reduces the visibility of the skies of Indonesia and the neighboring countries of Malaysia and Singapore. Singapore has been affected almost annually by severe smoke haze from forest fires occurring in many areas in Indonesia. Singapore was worst hit by the recent smoke haze that occurred in October 2015, when the hourly PSI readings hit a record high of approximately 471 (NEA Singapore, 2016). Two senior diplomats made the following comments in a local newspaper:

[10] Tan, Tam Mei, "*Haze is 'biggest environment crime' of 21st century*," The New Paper, November 4, 2015.

"*Once again, the forests of Kalimantan, South Sumatra and parts of Riau are on fire. The fires are destroying Indonesia's forests, rich biological diversity and natural heritage. The fires are also endangering the health of Indonesians, Malaysians and Singaporeans. The people most affected by the haze are Indonesians living in Kalimantan and South Sumatra.*

The haze is causing economic loss to the three countries. The fires are also causing harm to the world because of the carbon emitted into the atmosphere."[11]

Severe haze affects many aspects of urban life. In Indonesia, the country that is the source of these emissions, haze costs millions in economic losses tied to trying to extinguish the forest and peatland fires. The effects of the haze also spill over into the country's two closest neighbors (Malaysia and Singapore), generating negative externalities in terms of the drops in hotel room demand, flight cancellations, and school closures. If unabated, the haze problem could impede industrial development and economic growth (Brandt and Rawski, 2008). For urban residents, the prolonged exposure to haze could also have serious health and social impacts, which include illness and death.

Daily activities are likely to be interrupted during the haze periods. The government, through its NEA,[12] makes haze pollution information freely available to the public. The NEA reports and disseminates one-, three-, and 24-hour PSI readings on a regular basis to inform residents of air quality via mass media, such as television, radio, the Internet, and mobile applications. The PSI is a composite measure of the concentrations of multiple pollutants, which include particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), O_3, and CO.[13] The PSI readings provide a more accurate and comprehensive measure of air pollution than a single pollutant reading does. For ease of reference, the NEA also provides five different PSI descriptors to indicate the levels of pollution risks based on the PSI measures:[14]

[11] This was extracted from an opinion piece (by invitation) published in the Straits Times, "*The Haze, international law and global cooperation*," on Oct 6, 2015, by Professor S. Jayakumar, the Chairman of the International Advisory Panel, and Professor Tommy Koh, the Chairman of the Government Board, The Centre for International Law, National University of Singapore.

[12] A statutory body of the Singapore's government that is responsible for protecting the environment from pollution, maintaining a high level of public health and providing timely meteorological information. This agency is responsible for providing timely haze alerts and advisories to help households deal with the transboundary haze risks and shocks in Singapore.

[13] $PM_{2.5}$ is the most hazardous pollutant, which, if inhaled deep into the lungs, could enter into the bloodstream and cause complications to the respiratory and cardiovascular systems (Chang et al., 2016).

[14] Source: http://www.haze.gov.sg.

PSI Value	PSI Descriptor
0-50	Good
51-100	Moderate
101-200	Unhealthy
201-300	Very unhealthy
Above 300	Hazardous

On the days when the PSI levels are in an unhealthy range, the NEA will update the PSI readings every hour and issue haze alerts to all residents to advise them to reduce their exposure to the pollution outdoors. The NEA's advisories to residents include simple daily tips, including to wear masks, long-sleeved shirts, and pants when they are outside; to drink more water to flush out any toxins absorbed through their skin and lungs; to wash their hands and faces; and to shower immediately after outdoor activities. Social media sites, such as Facebook, Twitter, and Instagram, are informal, but popular, channels used by people to share haze-related information. We collect real-time tweets and analyze their frequency and context to provide an alternative measure of the human perceptions of air pollution.

During air-pollution events, some households may adopt a passive approach, hoping that the government will implement swift steps to stop the haze and smoke from forest fires. However, other households take more proactive approaches by taking steps to mitigate the impacts of air pollution on their health. Individuals who stay indoors are more likely to shut their doors and windows to keep the haze and pollutants out of their houses. In Singapore, where a typical day's temperature is approximately 30 degrees Celsius and shows little variation, households that keep their windows and doors shut are likely to turn on fans, air conditioners, and/or air purifiers to maintain a comfortable indoor environment that is clear of hazardous pollutants.

Staying indoors instead of going outdoors is a form of risk-avoidance that can be taken by residents to minimize their exposure to outdoor pollution. During the haze periods, individuals who spend longer periods indoors with their windows and doors closed and their air conditioners on are likely to use more electricity and to use more water in cleaning, showering, and washing clothes as well as in cooking at home, since the number of individuals eating out is reduced during haze periods. Therefore, we hypothesize that household utility (both electricity and water) consumptions are positively correlated with the amounts of time spent indoors.

Our study is designed to examine whether individuals change their usual daily activities and stay indoors outside of school and working hours on weekdays and during non-working weekends. Risk-avoidance behavior can be identified from the household utility consumption for the days "with" and "without" high haze pollution via the difference-in-difference framework. By using the matched hourly household utility consumption and pollution data, we empirically test the underlying mechanisms driving the avoidance behaviors of individuals who are exposed to and informed of the haze pollution events. The testable hypotheses are defined in Section 5.

4. Data Sources

For the purposes of testing the effects of air pollution on the daily life of urban populations, we need to both identify the appropriate outcome variables to measure changes in individual behaviors and find comparable pollution indicators that are available with the same frequency. We collect data from multiple sources, but the data can be grouped into two broad categories: outcomes of human activities and measures of ambient conditions.

4.1. Outcomes of Daily Human Activities

a. Household Water-Consumption Data

We obtain a unique dataset containing the hourly water-consumption records of a random sample of 376 households from public housing flats[15] from Singapore's water agency, the PUB. The public housing households were randomly selected in the automated meter-reading experiment, such that the real-time water meter readings of these households were recorded and collected for a 36-month period (26,304 hours) between January 2012 and December 2014. The panel data contains 8,537,868 observations. For each sample household, we have information about their hourly water consumption, ethnicity, and the floor level of the unit. In total, the sample includes 314 (83.5%) Chinese households, 38 (10.1%) Malay households, and 24 (6.4%) Indian households, a composition that closely mirrors the overall racial composition of Singapore's residential population.[16] The richness of the high-frequency water-reading data over this long time period gives us the flexibility to exploit the variations in the consumption patterns within the day, within the week, and within the month (with different weather conditions) in our analyses.

b. Electricity Consumption Data

We collected the average monthly electricity consumption data in kWh at the building level (where each building is identified by a unique postal code in Singapore) for all public and private residential buildings in Singapore for the period between January 2013 and December 2015. The data are provided by the EMA in Singapore and consist of 469,808 building-month observations. Figure 1 shows the distribution of residential buildings across the island, superimposed with the demarcation of the five NEA air-quality reporting regions (north, south, east, west, and central Singapore). We use the ArcGIS tool to sort the buildings by postal code into each of the NEA's air-quality monitoring regions. We aggregate the average monthly electricity consumption of the four different dwelling types (one/two-, three-, four-, and five-room/executive) to derive the building-month panel electricity consumption data.

[Insert Figure 1 about here]

[15] Public housing flats are built and sold by the government through its public housing agency, the Housing and Development Board (HDB), at subsidized prices. Public housing is sold only to Singaporean citizens who meet a set of income and family-related eligibility criteria.

[16] The ethnic distribution of Singapore's residence population is estimated at Chinese: 74.3%; Malay: 13.3% and Indian: 9.1%, based on the Department of Statistics' figures in 2014.

c. Hotel Performance Data

We collect daily hotel performance data, which includes hotel room rates and occupancy rates of a sample of 33,472 hotel rooms in 2015, as an alternative outcome measure to assess the economic losses associated with environmental externalities in Singapore. The hotel room samples account for approximately 76.8% of the hotel rooms in Singapore as of June 30, 2016. The daily hotel performance indices are obtained from STR, a data analytics company that tracks hotel performance in Singapore. The hotels are sorted by class segments into Upper Midscale, Midscale, and Economy as well as by geographic area into Marina Bay, Sentosa, Orchard, and River Valley. Further, 73% of the sample hotel rooms are located in the central region of Singapore. Hotels located outside of the central region are excluded from the sample due to the unavailability of data.

4.2. Weather and Haze Data

a. 24-Hour PSI Readings

There are five air pollution and weather monitoring stations located in the north, south, east, west, and central regions of Singapore that provide updated information on air pollution. The 24-hour PSI value provides an hourly indication of the air quality by averaging the data collected over the past 24 hours. We plot the 24-hour PSI readings from January 2012 to December 2015 in Figure 2. 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. We use a linear interpolation method to address the missing observations, and this approach may reduce the precision of the pollution measures. We explore different methods, which include using two different subsample periods—between August 24, 2012 and December 31, 2014 and between June 20, 2013, and December 31, 2014—and aggregating the hourly PSI and water-consumption records into their daily frequencies as robustness tests.

[Insert Figure 2 about here]

b. Weather Information and Haze Indicator

Poor weather conditions could be possible confounders of the influence of air pollution in households' decisions to stay indoors. To resolve this potential endogeneity issue, we collect the hourly weather data from The Weather Company, the world's largest private weather enterprise. The data are retrieved from two weather stations located in the northeastern region of Singapore (Seletar and Paya Lebar) for the period from January 2012 to December 2015.

The data contain hourly information on temperature, dew point, humidity, pressure, visibility, wind direction, and wind speed. The data also include 18 weather keywords used to indicate the weather status of each hour. Based on these keywords, we create the "*BadWeather*" indicator, which has a value of 1 when the hourly weather status contains the keywords of "heavy rain," "heavy rain showers," "heavy thunderstorms and rain," "rain showers," "thunderstorm," and "thunderstorms and rain," and 0 when the keywords include "clear," "light rain," "light rain showers," "light thunderstorms and rain," "mostly cloudy," "overcast," "partly cloudy," "rain," and "scattered clouds." The weather status indicators also contain three haze-related keywords, which are used to measure the severity of the haze: "light haze," "haze," and "heavy haze." The hourly "haze" indicators can be used as a supplement to the 24-hour PSI reading.

The data also contain a variable that measures visibility, based on the distance at which an object or light can be detected. The visibility is measured in a range from 0 to 10, where 0 indicates no visibility and 10 indicates very clear visibility. Visibility is affected by particles and gases in the atmosphere that absorb and deflect light. Figure 3 plots the daily visibility levels and haze statuses from 2012 to 2015.

[Insert Figure 3 about here]

In addition, we collect high-resolution daily weather records from various weather stations in Singapore from the NEA. Figure 1 illustrates the geographic locations of the weather stations. Thirty-nine weather stations (yellow circle) located in different subzones collect daily rainfall and temperature records, and 13 weather stations (black star) report wind data. The daily weather data is further aggregated into monthly frequencies. We use ArcGIS to locate the weather station closest to each residential building and collect the temperature, rainfall, and wind data from the nearest weather stations. Other island-wide weather measures, such as monthly averages of bright sunshine hours and relative humidity, are also collected.

c. Social Media (Twitter) Data

The perception of air pollution by households may differ from the NEA's PSI readings, which represents an objective measure of the severity of haze pollution. To measure the perceptive views and feelings toward the haze risks, we collect social media data from the Twitter accounts of public users who were based in Singapore for the period from January 1, 2012 to December 31, 2015. Private users' Twitter accounts are not open to the public and, thus, are excluded from this study. We analyze several aspects of social media activities, including tweet activities, tweet responses, and emotional states. Based on the haze-related keywords in the Twitter data, three types of activities are defined: "Haze," "Environment," and "Health." "Haze" is represented by a set of keywords: "haze," "hazy," "NEA," "psi," and "Singapore haze." "Environment" includes the keywords of "forest," "fire," "smoke," and "burn." Finally, "Health" includes the keywords of "asthma," "breath," "respiratory," "n95," and "mask."

We measure the total number of tweets that contain the above keywords per hour and their responses; for instance, we include the number of likes and forwards. Using the sentiment analysis technique,[17] we analyze the contents of the tweets and assign each tweet an emotion score ranging from -1 to 1. An emotion score of -1 in a Twitter post indicates the strongest negative emotion, while a score of 1 indicates the strongest positive emotion; a score of 0 indicates a neutral feeling. Figure 4 shows the daily tweets generated by Singapore users during the major haze episodes.

[17] The technique has also been used by the Living Analytics Research Center, at Singapore Management University (2014) to analyze people's subjective responses to the haze events. "HAZE in the eye of social media." *Palanteer*, Living Analytics Research Center, Singapore Management University, 2014. Web. 17 July 2016.

Figure 5 shows the proportion of tweets with negative emotions posted every month, which account for as much as one-third of all haze-related tweets during the peak haze hours.

[Insert Figure 4 about here]

[Insert Figure 5 about here]

5. Empirical Methodology and Strategy

5.1. Identifying Haze Episodes

The continuous hourly 24-hour PSI readings are the most direct way of measuring the haze intensity, as these measurements are less volatile than the spot hourly PSI reading (one-hour PSI reading, which were reported only after 2017) because the 24-hour reading is an hourly measure over a rolling 24-hour period. Therefore, our sample of hourly haze measurements does not contain observations greater than 300, which is considered "hazardous" to human health.

We conduct an empirical analysis on an hourly, a daily and a monthly basis. Since the 24-hour PSI reading at 12 am is the average of the past 24 hours, we use this value as the daily average. Further, we convert the daily average PSI readings into the monthly averages to perform an analysis of the monthly water and electricity consumption data. During the study period, the extreme haze episodes lasted only for a few days, and the averaging method was used to compute the average monthly PSI readings, which could have caused significant smoothing of the PSI value; thus, the monthly readings are less volatile than the spot daily PSI readings.

We also use the data from The Weather Company and Twitter to obtain four alternate measures of the haze episodes. In the weather dataset, we create a binary indicator of haze when the weather status contains certain keywords, such as "light haze," "haze," and "heavy haze." We also define a categorical variable, which has a value of 1 for "light haze," 2 for "haze," and 3 for "heavy haze," to represent the intensity of the haze experienced by the studied households. Moreover, the hourly visibility measurements, which range from 0 to 10, are an alternative indicator of air quality. Further, the Twitter data provides a continuous measure of the public consciousness of haze conditions, which are subjective and more perceptive in nature when compared to the objective 24-hour PSI readings.

5.2. Empirical Models

First, we use ordinary least squares regressions to investigate the reduced-form relationships between the different haze measurements (hourly, daily, and monthly 24-hour PSI readings, as well as a binary indicator of haze, category variable of haze, hourly/daily visibility, and daily haze-related tweets) and household energy consumption. Our basic reduced-form regression model is as follows:

$$(1).\ Y_{i,t} = \beta \times Haze_{it} + X_t + \tau_t + \alpha_i + \epsilon_{i,t}.$$

Here, the dependent variable, $Y_{i,t}$, is the periodic logarithmic term of the water consumption for each household i at the end of hour t. $Haze_{lt}$ is the logarithmic term of the air-pollution level at each weather station l from 2012 to 2015. β captures the average periodic energy consumption during the haze episodes. This first step allows us to predict how changes in utility consumption are associated with the percentage increases in the 24-hour PSI reading. X_t is a vector of the control variables, which include the logarithmic terms of temperature and humidity. τ_t is the annual fixed effect and monthly fixed effect, which are used separately to absorb the time variations of the water-consumption trends and to average out all the other concurrent aggregate factors. Finally, α_i is the household fixed effect dummy, which is included to absorb the systematic differences in the water usage preferences at the household level.

In addition, we study the dynamics of the water-consumption responses following Agarwal and Qian (2014) by estimating the following distributed lag model:

$$(2).\quad Y_{i,t} = \sum_{-a}^{b} \beta_{a+b} \times \ Haze \times 1_t \ + Haze_{i,t} + W_{i,t} + \ \tau_t + \alpha_i + \epsilon_{i,t}.$$

Here, the coefficient β_0 measures the immediate water usage response during a haze period. $[\beta_1,\ldots, \beta_b]$ are the marginal coefficients that measure the additional responses from the current period up to period b after the haze event. Similarly, the coefficients $[\beta_{-1},\ldots, \beta_{-a}]$ capture the changes in the water-consumption trends from period a before the haze event. 1_t is a binary variable that is equal to 1 in period t. To examine the cumulative impact of haze episodes on water consumption, we use the cumulative coefficient β_{a+b} to describe the cumulative response of water usage after the $a + b$ period. For instance, when the water-consumption increases by β_0=0.19 during the haze shock and rises by β_1=0.07 one period after the shock, then the cumulative consumption increases by 26% on a 100% increase in the 24-hour PSI value. We also measure the cumulative water consumption before the haze episodes, and we expect the coefficient to be economically and statistically insignificant.

All standard errors are robust and are clustered at the household level (for water-consumption analysis) or at the building level (for electricity consumption analysis), which allows an arbitrary variance-covariance matrix to capture the potential serial correlations in the residual error terms.

5.3. Testable Hypotheses on Risk-Avoidance Behavior

Utilizing the hourly household consumption and pollution data, in this section, we explain the mechanism by which the haze effects impact water and electricity consumption. To better understand household utility consumption on haze days, we examine the relationship between water consumption and haze levels in a day (6 am to 6 pm) and at night (6 pm to 12 am) on weekdays and weekends separately.

Avoiding air-pollution episodes requires one to stay indoors, which is costly for those who are full-time employees and students. We construct the following three hypotheses to describe the changes in household water consumption with respect to household behaviors during haze episodes to establish evidence of risk-avoidance behavior in households.

Hypothesis 1*: On weekdays, water usage remains unchanged during the day and increases significantly at night.*

Households face a trade-off between the health benefits of staying at home and the salary or educational gains of going to work or school. As employees and students need to commute, the opportunity costs of avoiding air pollution are relatively high during weekdays. Households who have been exposed to ambient air pollution are more likely to clean more regularly and thoroughly after work or school. The probabilities of households taking longer showers, washing their clothes more regularly, and cleaning their homes more frequently increase. Hence, while the household water-consumption behaviors remain unchanged during the day, the water usage behavior may change at night due to the daytime exposures to haze.

Hypothesis 2: *On weekends, when most households choose to go outdoors, water usage remains unchanged or decreases during the day and increases significantly at night. When households choose to stay at home to avoid exposure to air pollution, the change in water usage is ambiguous and needs to be tested.*

The opportunity costs of risk-avoidance for households are relatively lower on weekends, when most households do not have work or school commitments. During weekends with haze episodes, households are likely to stay indoors (e.g., home, shopping mall, community center, or a friend's home) to avoid exposure to air pollution. These risk-avoidance behaviors are particularly prevalent when the government announces a pollution warning through its website or other mass media channels. If households are accustomed to spending time indoors, their usual behaviors may not change in response to the exogenous haze shocks; otherwise, they may choose to go out despite the pollution warning. Households sensitive to their utility bills may choose to go out and enjoy free air-conditioning environments at shopping malls or community centers. If households go out during the day on weekends, we would expect an increase in water usage for washing and showering after they return home.

However, when the haze risk level is "hazardous" and households are strongly advised by the government to stay home, the change in water consumption during the weekend is ambiguous. Households turn on air conditioners or fans to lower the room temperature, but the necessity of taking longer showers and washing more clothes decreases. However, more water may be used for cleaning and cooking during the day. Therefore, the change in water usage is uncertain. Understanding how households respond to haze on weekends remains crucial.

Hypothesis 3: *On weekends, when households choose to travel abroad, water usage decreases during both the day and night.*

Some households may even choose to travel abroad to get away from the haze. When households do not stay in Singapore, the consumption of both electricity and water decreases. However, we are unable to test this because the data do not contain information on whether the households stay at home. Moreover, the possibility of households traveling on weekends only decreases the water and electricity usage; therefore, the estimated impact of air pollution on utilities on weekends could be a lower-bound estimate.

In summary, to examine the three testable hypotheses (i.e., to support the risk-avoidance behavior hypothesis), we expect the coefficients that measure the impacts of haze on water consumption to be significantly positive at night on weekdays, insignificantly positive during the day on weekdays, and significantly positive at night on weekends. The sign of the coefficient of the effects is uncertain during the day on weekends; when the coefficient remains positive during the weekend day, we can assert that the households' decision to stay at home leads to an increase in water consumption during the weekend day as opposed to during the weekend night.

6. Main Results

6.1. Haze Effects on Water Consumption

First, we examine the causal effects of the haze pollution that occurred from 2012 to 2014 using data on the hourly water consumption and the hourly 24-hour PSI data. The baseline results, as shown in Column 1 of Table 1, show a highly significant positive response in the hourly water consumption in relation to the change in the 24-hour PSI reading, as predicted by Equation (1). Using all observations, we estimate that a 100% increase in the 24-hour PSI reading causes hourly water consumption to increase by 5.10%. To control for the differences in the water consumption at peak versus off-peak hours, we include the hourly period fixed effects, where the within-the-day variations of water consumption are controlled for using four subperiods of the daily water-consumption data: 12 am to 5 am, 6 am to 11 am, 12 pm to 5 pm, and 6 pm to 11 pm. When we control for the hourly period fixed effects in Column 2, the incremental water-consumption values are significant but have a lower rate of 2.89% when the hourly 24-hour PSI reading doubles.

[Insert Table 1 about here]

The weather conditions could influence the haze effects, and thus, we try to separate the possible confounding effects of weather conditions from the haze pollution. Using information obtained from The Weather Company, we drop the time periods during which both haze and "bad" weather conditions coexist, as identified by the data. We drop 2,077 observations, and the regression results from a small number of observations (subsample 1) are summarized in Columns 3 and 4 in Table 1 (with hourly fixed effects). The regression results are very similar to those of the full-sample analysis, and the haze-induced increases in water consumption remain positive and significant. Next, we further exclude the days with "bad" weather conditions, that is, we keep only the observations during normal weather conditions and haze periods (subsample 2), and the results of this smaller sample size show that the haze effects are still positive and significant; however, a smaller increase in the hourly water consumption, specifically that of 2.76%, were recorded during the haze shocks. Moreover, the haze-induced water-consumption responses disappear when the hourly fixed effects are controlled for in Column 6.

Figure 2 plots the daily average PSI readings (blue line – top) and the first difference of the daily PSI readings (red line - bottom) (month-to-month changes) for the period from January 2012 to January 2015. The short-term air pollution shock occurring in mid-June 2013 is shown in the corresponding spike of the two charts. The hourly 24-hour PSI readings, as reported by the NEA, are smoothed readings that may underestimate the real-time haze pollution in the air, and the use of the smoothed PSI measurements may underestimate the effects of air pollution on water consumption. According to the US Environmental Protection Agency, haze occurs when sunlight is filtered or deflected by tiny pollution particles, and thus, the clarity and color of the air is greatly reduced. Further, the visibility in the skies is particularly low during humid weather conditions.

We use three different measures of weather conditions, which are visibility, temperature, and humidity as provided by The Weather Company, as indirect proxies of the haze shocks. Figure 3 shows the daily visibility measurements (blue line - top) (with values ranging between 0 and 10) and the number of "haze" statuses per day (red line – bottom) as reported in the weather status reports of The Weather Company. With these alternate haze proxies, we estimate the water-consumption responses using Equation (1) and report the results in Table 2. In Column 1, where the hourly water-consumption data are used in the model, the *ln(visibility)* coefficient is negative and significant, which implies that when the visibility level is halved during haze days, the average hourly water consumption increases by approximately 3.14%. When the effects are measured at a daily level, the coefficient of *ln(visibility)*, as shown in Column 2, is still significant at the 5% level, and the magnitudes of the water-consumption responses are relatively larger. In other words, when the visibility level is halved (i.e., when the haze level doubles), household water consumption increases by 10.9%. The temperature variables have significant and positive coefficients, but the humidity coefficients are insignificant in predicting both hourly and daily water consumption in the models. The visibility and temperature can be used as indirect proxies of the haze effects, which produce significant responses in water consumption.

[Insert Table 2 about here]

We replace the smoothed 24-hour PSI readings with [*Haze_Indicator*=1], which is derived from the keywords of "light haze," "haze," or "heavy haze" as reported in the hourly weather statuses in The Weather Company's database. In addition, we estimate the water-consumption models in Table 2(B). Column 3 reports the results estimated using the full-sample set, whereas Column 4 reports the results estimated using a smaller subsample, where the periods with "bad" weather conditions and visibilities of 2 or below are dropped. The coefficients of *Haze_Indicator* in Columns 3 and 4 are statistically significant, and the magnitudes of the two coefficients are similar, which supports a 4.3% increase in water consumption during the haze shocks. Column 5 uses a smaller sample of the daily weather keywords, as opposed to the hourly keywords of Columns 3 and 4, and the haze-shock effects are much stronger and statistically significant.

Next, we look at the dynamics of the consumption responses as a function of the pollution shock. Following Equation (2), we study the dynamic relationship between the temporary changes in air quality and the behavioral changes of households in the post-shock periods. Figure 6 shows the weekly water-consumption trend (Panel A), and the one-week-long haze period occurring over the third week of June 2013 is identified as week "77," whereas the other numbers correspond to the 13-week window before and after June 2013 (week 77). We observe a sharp rise in the weekly water consumption during the period when the haze started in week 76 and when the haze hit its peak in week 77.

For the purpose of the dynamic analysis of the weekly water-consumption responses, we use an "event study" approach that denotes the haze week in June 2013 as the event week (t=0) and considers the six-week pre-haze (t=-6 to t=-1) and post-haze periods (t=1 to t=6). The effect increases slightly as soon as the households become aware of the haze in week 76 and jumps sharply in week 77 when the haze reaches an extremely high level. The coefficient β_0, which is equal to 0.17, quantifies the immediate water usage responses during the haze period. The estimated coefficients are statistically 0 during the pre-haze periods. β_{-1} and β_1 are equal to 0.074 and 0.078, respectively. As the air pollution experienced by the households is likely to wear off quickly, the effects on consumption behaviors concurrently dissipate. We find that the behavior of increased water usage only lasts one week after the end of the haze episode. Panel B of Figure 6 graphs the entire path of the cumulative coefficients β_{a+b}, and the dashed lines represent the corresponding 95% confidence intervals. The results seem to suggest significant "rebound" effects of the water-consumption responses of households to the short-term air-pollution events, which persist for only one week. People may revert to their usual daily norms after the haze has dissipated.

[Insert Figure 6 about here]

6.2. Risk-Avoidance Behavior: Evidence from Hourly Water Consumptions

We find evidence of the risk-avoidance behaviors by examining the within-the-day hourly water-consumption behaviors of households during the haze periods. Household daily weekend activities (e.g., staying at home, going out, and traveling abroad) and weekday activities (e.g., going to work and attending classes) could influence the intraday (day versus night) variations of water consumption in response to the haze pollution. To better understand the household utilities consumption on haze days, we examine the relationships between water consumption and haze levels during the day (6 am to 6 pm) and at night (6 pm to 12 am) on weekdays and weekends. The water-consumption data from 1 am to 5 am are excluded to avoid a spurious relationship between haze measurements and water usage. While the haze level may increase significantly at night, most people are asleep during this time, which means that the water consumption stays low. Table 3 reports the estimation results using the hourly water consumption and haze data from January 1, 2012 to December 31, 2014.

[Insert Table 3 about here]

Columns 1 and 2 in Table 3 show that the effect of haze shocks on water consumption is significant and positive on weekends but insignificant on weekdays. Similar results are also found during the day, between 6 am and 6 pm on weekdays (Column 3) and weekends (Column 4). The coefficient of *ln(24-hour PSI)* is significant only when predicting weekend daytime water consumption but is insignificant when predicting variations in daytime water consumption on weekdays. The results are consistent with our expectations that the impacts of haze shocks on the daytime water consumption on weekdays are insignificant, as most people have to commute to work or school and do not stay at home between 6 am and 6 pm on weekdays. In addition, the significant positive response during the day on weekends suggests that households try to avoid exposure to air pollution by staying at home; as a result, water consumption increases.

For the nighttime water consumption between 6 pm and 12 am, the coefficient of *ln(24-hour PSI value)* in Columns 5 and 6 of Table 3 indicates that a 100% increase in the 24-hour PSI value is associated with 4.92% and 4.30% increases in nighttime water consumption on both weekdays and weekends, respectively. This impact is positive and significant for nighttime water consumption of both weekdays and weekends, when individuals return home and consume more water for cleaning and washing purposes. Based on the positive relationship between the haze level and water consumption, we could not reject the risk-avoidance hypothesis.

Table 4 presents the results of the water-consumption models on weekdays and weekends during an intensive haze period of June 2013 in Panels A and B, respectively. We include a binary variable, *Heavy_Haze*, in the model specification to represent different thresholds of the hourly 24-hour PSI values, ranging from 80 to 200. In Column 1, *Heavy_Haze* is equal to 1 when the 24-hour PSI value is greater than or equal to 80; otherwise, the value is equal to 0. We test four different cutoffs [80, 100, 150, and 200] to explore how household water usages respond to different levels of air pollution. We also include a binary variable, *Night*, which indicates the period between 5 pm and 12 am, and its interaction term, *Heavy_Haze*Night*, which measures the difference between the daytime and nighttime haze effects.

[Insert Table 4 about here]

The weekday water-consumption models are shown in Columns 1 to 4 of Table 4. The results show that the coefficient of the haze intensity dummy is significant and positive only when the 24-hour PSI hits 200 or more. The results imply that households stay indoors and use approximately 9.83% more water when the haze pollution reaches the "very unhealthy" and "hazardous" levels. The coefficients of the *Night* dummy variable show that water consumption after 6 pm is higher than that of the daytime on typical weekdays. However, during the haze periods, we find that nighttime water consumption increases by an average of 5.84% to 9.36% as indicated by the interaction term, *Heavy_Haze*Night*. These results are consistent with the household risk-avoidance responses, which are evident during the haze-shock periods. Individuals cannot easily avoid haze due to work or school commitments during the daytime on weekdays, and they tend to stay indoors after work or school to minimize haze risks; thus, they use more water at night on weekdays during the haze periods.

We use the same regression models to analyze the nighttime water consumption of households during the weekends, and the results are summarized in Columns 5 to 8 of Table 4. While the effects of haze shocks on water consumption on weekends are not significantly different, the nighttime water consumption is higher than the daytime consumption on weekends because households may still choose to go out during the day on weekends.

Most importantly, we find more discerning evidence of risk-avoidance when we study the interactions of the *Heavy_Haze* and *Night* variables in the models. The results in Column 5 show that households use 7.72% more water at night on weekends with mild-haze shocks, such that the hourly 24-hour PSI readings are more than 80. When the 24-hour PSI values reach 100 or more, the *Heavy_Haze*Night* coefficients are positive but insignificant, suggesting that the different haze effects are marginally different for the daytime and nighttime water consumptions on weekends. The results imply that when the haze risk reaches the "very unhealthy" (24-hour PSI>100) and "hazardous" levels (24-hour PSI>200), the risk-avoidance behaviors of households become highly significant. Households are more willing to minimize health risks by sacrificing their outdoor activities during weekends; therefore, they are more likely to refrain from going out on weekends at the expense of being exposed to haze risks.

6.3. Robustness and Falsification Tests

We perform robustness tests to further separate the possible confounding effects of weather conditions on household water-consumption decisions. For instance, households are more likely to use more water (e.g., take more baths) during warmer days. We construct a matched sample of treatment (hours with high 24-hour PSI readings) and control groups (hours with low 24-hour PSI readings) using the propensity score matching (PSM) methodology. For matching purposes, we create a *haze_dummy* to represent the treatment period, where the *haze_dummy* is equal to 1 when the hourly PSI readings at said period exceed the referenced cutoff and is 0 otherwise (the control period). We use four different cutoffs [24-hour PSI=60, 65, 100, and 150] to identify the treatment periods in our experiment.

In addition, we compute the propensity scores based on a logistic regression using a rich set of weather conditions, such as temperature, humidity, pressure, wind speed, and rain status. Household energy consumptions are notably different on weekends than on weekdays; therefore, the matching also considers the differences in the days of the week. Then, we perform nearest neighbor matching with replacement based on the computed propensity score to pair the treatment and control samples. The results are shown in the Appendix (Table A1). The PSM significantly reduces the post-matching differences between the treatment and control periods in all observable weather conditions.

We could reduce the selection bias when estimating the water-consumption response models using this balanced panel of treatment and control periods, which share similar weather conditions. In the robustness checks, we use four different subsets of matched samples to rerun Equation (1) and present the results in Table 5. Column 1 shows the results of the full-sample analysis without matching, which predicts that as the haze intensity doubles, as represented by the *ln(24-hour PSI)* variable, the water consumptions of the households increase by 2.89%. Columns 2 to 5 show the regression results using the PSM matched samples with different treatment cutoffs. When the mild-haze effects are examined using the lower PSI cutoffs of 60 (Column 2) and 65 (Column 3), the coefficients of *ln(24-hour PSI)* are significantly positive, which indicates that a 100% increase in the 24-hour PSI reading causes the water consumption to increase by 8.67% and 12.1%, respectively. The incremental responses in water consumption are insignificant when the more stringent PSI cutoff of 100 is used. The results imply that water-consumption behavior is positively influenced by gradual increases of the haze-shock intensities. Households are more sensitive to the haze shocks when the PSI readings go above 100. In other words, most households are less able to discern a PSI value of 100, which is in the “moderate” range, from a PSI value of 101, which is in the “unhealthy” range.

[Insert Table 5 about here]

Next, we perform falsification tests to further investigate possible confounders of water consumption by randomly selecting “placebo” treatment periods with no haze shocks. We re-estimate the models by randomly assigning 30 “placebo” haze days to each year for the three consecutive years to test household water-consumption responses. The randomization process is repeated over 500 times. Figure 7 shows the results of the randomization process and compares them with the findings of the actual "treatment" pollution periods. We find that the randomly assigned air-pollution periods do not have significant impacts on the household water-consumption behaviors. The top panel of Figure 7 presents the distribution of the estimated parameters with random assignments, whereas the lower panel shows the t-statistics of the falsification tests. The falsification tests show that the parameter estimates with the random assignments of haze episodes are normally distributed about 0, with most coefficients being insignificant, suggesting that the haze effects experienced in Singapore are unlikely to arise randomly.

[Insert Figure 7 about here]

6.4. Heterogeneity Tests

We run additional heterogeneity tests on the differential responses of households from different ethnic groups, dwelling types, and floor levels to the sharp jumps in the 24-hour PSI readings. Panel A of Table 6 presents the water-consumption responses by ethnicity, which includes Chinese, Indian, and Malay households. The results show that Malay households respond more strongly to haze shocks relative to the responses of the Chinese and Indian households. Panel B compares the water-consumption responses of households living in different dwelling types. We find significant and positive responses of households living in four- and three-room Housing and Development Board (HDB) flats (5.54% and 4.32%, respectively). The water-consumption responses are stronger for households with the bigger four-room units and are specifically estimated to be 1.22% higher than those of the households with the smaller three-room units.

[Insert Table 6 about here]

As dense suspended PMs in the haze are likely to precipitate nearer to the ground, households in the lower-level units are likely to be exposed to more "concentrated" pollutants (or blanketed by thicker haze pollution) than those in higher-level units. Nevertheless, some experiments conducted in China[18] have established that the concentration of air pollutants (e.g., PM_{10}, PM_5, $PM_{2.5}$, and PM_1) decreases with respect to building height, but the studies find different vertical distributions of the pollutants above ground level.[19] Panel C of Table 6 shows the results of the tests using samples from households of different floor levels. We find significant and positive responses of households in all the subsamples of households from flats below the 20^{th} floor. However, the responses of households living on the higher floors (between the 21^{st} and 25^{th} floors) are insignificant. These results are consistent with earlier findings that implied that haze pollutants are likely to be more dissipated in the air when the unit is above the 21^{st} floor.

6.5. Social Media Responses and Average Daily Household Water Consumption

[18] "Building Height and the Risk of Lung Cancer (2012)." *Hebei Technology University News*. 22 Feb, 2012. Web. 30 May 2016.

[19] Researchers at Tsinghua University, who studied the haze concentrations in Beijing from October to December 2003, show that large variations in the concentrations of $PM_{2.5}$ in the air are found in the range of eight to 32 meters above the ground (approximately between the second and 10^{th} floors of a building), and the $PM_{2.5}$ concentration decreases by 19% at a height of 64 meters from the ground (approximately at the 20^{th} floor). In a separate study conducted in the city of Shijiazhuang, Hebei Province, the average daily concentration of pollutants in the air was shown to be non-linearly distributed from 1.5 to 72 meters above the ground.

The role of emotions has been largely ignored in determining household energy consumption. Raghunathan and Tuan Pham (1999) posit that negative emotions may shape decisionmakers' motives and, thus, determine decisions. Therefore, Twitter data was collected as a proxy of the changes in emotions during the study period, providing a unique identification strategy to study the impact of negative emotions caused by air pollution on household energy consumption.

We use daily Twitter data to capture the personal emotions of households toward the haze episodes. From public Twitter accounts, we collected hourly haze-related tweets and assigned an emotion score to each of the tweets (ranging from -1 to 1) using the sentiment analysis technique.[20] Moreover, our Twitter-data analysis is based on the daily aggregation of hourly Twitter data. Figure 3 plots the tweet count per day (red line - bottom) and the change in the tweet count per day (blue line - top). Panel A in Table 7 presents the relationship between the number of haze-related tweets and water consumption using the full sample of tweets per day. Column 1 shows a significantly positive coefficient with *ln(Number of Tweets)*, indicating that water consumption increases as much as 7.11% when the number of haze-related tweets doubles. Column 2 uses only tweets with a negative emotional score to study the relationship between social media responses and water consumption, and the results show that a 100% increase of the number of negative daily haze-related tweets causes the water consumption to increase by 3.72%.

[Insert Table 7 about here]

Further, we sort the tweets by topic into three broad categories—"Haze," "Environment," and "Health" (see Figure 5)—and estimate the water-consumption response models in Columns 3 to 8 in Panel A of Table 7. We estimate the water-consumption responses to the Twitter scores as having magnitudes varying from 1.01% for the "Haze" category to 12.3% for the "Environment" category. When we use only the tweets with negative emotions, the "Environment" category (Column 6) generates stronger water-consumption responses of 6.42%, which suggests that households who tweet more on the issues related to the environmental impact of wildfires show stronger responses in their water consumptions. Next, we use only the tweets that have been "liked" or "retweeted" (shared), and replicate the early analyses. The results are summarized in Panel B of Table 7. The number of observations drops significantly, and most of the coefficients of *ln(Number of "Likes" or "Retweets")* are positive; however, some are insignificant. Still, the increases in the number of "Likes" and "Retweets" in the tweets that are related to "Environment" and "Health" topics show significant and positive effects on water consumption, ranging from 2.68% to 3.34%, respectively. The Twitter-data analyses indicate that Singaporeans closely monitor air-pollution events via social media responses and are particularly strongly concerned with issues relating to the "Environment" and "Health" effects of air-pollution.

7. Other Empirical Results

7.1. Responses of Electricity Consumption

[20] We perform a sentiment analysis and decode the tweet contents using "TextBlob," a Python library for processing textual data, which provides a simple API that could support some common, natural language processing tasks.

We collect panel data of the building-level monthly electricity records for 4,200 private and 9,336 public residential buildings; the data are available on a monthly frequency, covering the period from 2013 to 2015. Using monthly building-level electricity consumption as an alternative outcome variable, we test the average household responses of monthly electricity consumption to the change in the monthly average 24-hour PSI readings using the same model structure as Equation (1). Table 8 presents the regression results by progressively including more pollution and weather measures. The haze effects, as represented by the *ln(PSI)* variable, are statistically and economically significant in all models. In Column 5, where we control for the monthly average temperature, total rainfall, sunshine hours, average wind level, and relative humidity, the results show that a 100% increase in the monthly average 24-hour PSI value increases the building-level electricity consumption by 2.34%. Table A4 presents the electricity consumption responses by room type, which include 1-or-2-room, 3-room, 4-room and 5-room or Executive HDB. The results show that households living in smaller units (1-or-2-room HDB) are less sensitive to the haze shocks than the households living in larger HDB flats. Larger flat types (usually with larger household sizes) are more likely to have elderly residents or children, who are sensitive to air pollutants and, thus, exhibit stronger avoidance behaviors during haze episodes by increasing their electricity consumption more than smaller flat types (usually occupied by single or married but without children residents).

[Insert Table 8 about here]

We run a series of robustness tests; due to the spatial constraints, the results are reported in the Appendices. Like Raghunathan and Tuan Pham (1999), we use the negative emotional scores from the Twitter data as an alternative measure of the haze shocks and find that, with the tweets expressing negative emotion, a 100% decrease in the emotion score percentage (people's dissatisfaction with the haze condition increases) is associated with a 12% increase in household electricity consumption occurs (see Table A2 in the Appendix). Based on both the private-housing and resale-public-housing transaction price data, available from public sources,[21] we sort the sample buildings by building-level-per-square-meter housing prices into four categories and then conduct the water consumption and haze effect tests (see Table A3 in the Appendix). We find that households in lower-price houses respond more significantly and strongly to the haze shocks than those in higher-price houses. If unit housing prices are a reasonable proxy for household wealth, we may infer that the haze-shock effects on electricity consumptions are stronger in the low-income households and are marginally smaller for wealthier households. More future tests could be conducted to study the income effects on the responses to air-pollution risks.

Next, by merging the monthly electricity consumption data into the aggregated monthly water consumption data of the nine experimented HDB buildings (where automated water meter readings are available) for the period between January 2013 and December 2014, we test the cross-domain relationship between water and electricity consumption. The results, which are reported in the Appendix (Table A5), affirm that water and electricity are complementary consumptions for households during the haze periods. The cross-elasticity of water consumption with respect to

[21] The private transaction price data are obtained from the "REALS" system of the URA of Singapore, whereas, the resale-public-housing transaction price data are obtained from the database of the HDB. Both public agencies publish timely real-estate transaction data.

electricity consumption is significant, indicating that a 1% increase in building-level electricity consumption is associated with a 0.542% increase in building-level water consumption.

Moreover, we analyze the dynamic monthly electricity consumption trends when Singapore's skies were first shrouded by the haze during the first week of September 2015. We plot the dynamic monthly (Panel A) and cumulative month-to-month electricity consumptions (Panel B) in Figure 8 and do the same for a seven-month window that spans the duration of the second heavy-haze episode that occurred in Singapore between September 2015 and October 2015. The two months with the haze shocks are coded using the annual-monthly variable with the corresponding numbers of "668" (September 2015) and "669" (October 2015).

We find that persistent and high levels of electricity consumption were reported (Panel A) and that the slope of the months of September (668) and October (669) of 2015 was steeper in the cumulative chart (Panel B) during these two months with serious haze shocks caused by forest fires from Indonesia. The two-month high and persistent levels of electricity consumption show the significant behavioral responses (inelastic in electricity consumption) of households to the haze shocks. Moreover, households continued to use more water and electricity after the haze clears.

The long-term haze episode, which lasted for two months, impacted household consumption habits and caused the electricity consumption levels to continue rising in the two months following the long-term shocks. While the risk-avoidance behavioral responses are not transitory, we do observe rebound effects after the haze shocks. Future works could study the asymmetric differential responses of the haze episodes and normal periods.

7.2. Hotel Performance Outcomes and Haze Shock

The exogenous haze shock from Indonesia could have had an adverse economic impact on the source and neighboring countries. The haze outbreaks reduced visitor arrivals and inflicted significant economic losses on the tourism industry in Singapore. In this section, we use the daily hotel room rates and daily occupancy levels as outcome variables to assess the economic costs of air pollution. The current and lagged haze effects on the changes in the daily hotel room rate and daily hotel occupancy are modeled using the following specification:

$$(3).\ \ Y_{i,t} = \beta \times \ Haze_{i,t} + \gamma \times \ Haze_{i,t-n} + \delta \times XE_t + \lambda \times STI_t + \tau_t + \alpha_i + \epsilon_{i,t}.$$

Here, $Y_{i,t}$ is the logarithmic term of the daily room rates and daily occupancy levels for a hotel sample *i* sorted by class, [Upper Midscale, Midscale, Economy], and region, [Marina Bay, Sentosa, Orchard, River Valley], at t. $Haze_{lt}$ is the logarithmic term of the daily, average air-pollution level reported at the three PSI measurement stations (central, east, and south). β and γ capture the immediate and lagged effects of air pollution on hotel performance. δ is the coefficient vector of the foreign exchange rates, *XE*. λ is the coefficient of the log of the Singapore's Straits Times Index (stock market indicator). α_i is a hotel-class and hotel-location fixed effect. τ_t is the monthly, yearly and daily fixed effects that account for variations of hotel performance indices over time. Finally, $\epsilon_{i,t}$ is an error term to allow for serial correlation in the hotel performance indices.

We use the daily indices of the hotel room rates and the occupancy rates constructed by the Smith Travel Resource, which cover a representative sample of 76.8% by class and 73% by region, respectively, of all hotels in Singapore (see Table A6 in the Appendix). We use the daily exchange rates to control for the levels of tourism expenditure in the hotel performance models. We include only the daily exchange rates of Singapore's top three tourism-receipts-generating[22] markets, which are the Indonesian Rupiah ("IDR"), Chinese Yuan Renminbi ("CNY") and Indian Rupee ("INR") against the Singapore Dollar ("SGD") as control variables in the models. In addition, the US dollar ("USD") is included to account for external global economic growth; the natural log of the stock market indicator, the Straits Times Index ("STI"), is also included to capture Singapore's economic growth. The exchange rates and stock-market-index data are collected from the Bloomberg database.

First, we examine the hotel room occupancy (demand) models in Table 9 (by class) and Table 10 (by region) and test the demand responses to the haze outbreak in October 2015. Most hotels impose a penalty on same-day cancellation, and thus, we use lagged haze shocks in the models. The results of the two hotel demand models show consistent results and that the coefficients of the lagged haze shocks, $PSI_{t=k,}$ where k=[-6, -5, …, -1], are generally significant and negatively affect the hotel occupancy rates. The results imply that hotel demand is significantly and adversely affected by the lagged haze shocks. Since most hotel cancellation policies include penalty fees for same-day cancellations, the haze measures do not affect the hotel occupancy levels of the initial haze period (the coefficient $PSI_{t=0}$ remains economically and statistically insignificant).

[Insert Tables 9 and 10 about here]

Based on the daily data covering the period spanning the two-month haze outbreak in 2015, we estimate the relationships of hotel performance with the concurrent and lagged haze shocks in the models. The results of the hotel performance models are separated by class (Panel A) and region (Panel B) and are summarized in Table 11. The coefficients of the concurrent haze shock, (*ln_PSI*), and the lagged haze shock, (*L1.ln_PSI*), are significant and negative across all four models. The results predict that the daily hotel room rates decline by 1.99% (by class) and 1.82% (by region) when the contemporaneous 24-hour PSI readings double; the daily hotel room rates decline by a smaller magnitude of 1.54% (by class) and 1.31% (by region) when the daily average of the lagged 24-hour PSI readings doubles.

[Insert Table 11 about here]

The declines in the daily occupancy rates and daily hotel room rates for hotels in Singapore represent the economic losses endured by hoteliers during the haze periods, which are business risks beyond their control. More importantly, the negative performances of the hotel industry during Indonesia's forest-fire periods could be positive evidence indicating the risk-avoidance of foreign visitors, who shun the haze that "shrouds" the skies of Singapore.

7.3. Externality Costs of Transboundary Haze

[22] The expenditure share of the accommodation sector made up more than 20% of the total tourism receipts in 2015 (Quote STB).

This paper utilizes outcome variables from the daily life of a household to measure the impact of air pollution on everyday life, which affects a substantial part of the economy but has been ignored in the existing literature. Our findings from our baseline model suggest that, as the haze readings double, the household-level hourly water consumptions increase by 5.1% and the building-level monthly electricity consumptions increase by 2.34%. Moreover, a haze outbreak creates significant negative externalities for hotel performance. Given this information, placing our findings in a larger context and providing an informal estimate of the economic costs in order to value and quantify the partial economic-welfare effects of haze on the urban population in Singapore.

The computations are based on two scenarios: (1) a mild-haze shock, where the PSI readings increase by 100%, and (2) an extreme haze shock, where the PSI readings increase six-fold (500%); a linear relationship is assumed between the PSI readings and utility consumptions. In Scenario (2), when the PSI readings increase from 50 to 300, the hourly water consumption per household and monthly electricity consumption per building will increase by 25.5% and 11.7%, respectively, on a linear scale.

Using the informal estimation method, we convert the increases in water and electricity consumption into the economic costs[23] of the negative externalities caused by the forest fires in Indonesia. We obtain the water and electricity consumption statistics from the Department of Statistics and derive the estimated nation-wide monthly consumptions of water and electricity. Then, we apply the appropriate tariff rates to derive the estimated externality costs for a one-month haze shock in Singapore.

Based on the annual sales of domestic potable water of 219,200,000 m^3 in 2014, we derive the monthly water consumptions by Singaporean households to be 24,266,667 m^3. Given that the current water tariff for an average consumption of 40 m^3 and above is \$1.40 per m^3 and the water conservation tax is 45%, and given the other fees, including the waterborne fee and sanitary appliance fee (approximately 5%), the per m^3 water cost for a typical household is assumed to be approximately \$2.10 per m^3. We apply the per m^3 water cost to derive the externality costs of Scenario (1) (S\$2.60 million, US\$1.83 million) and Scenario (2) (S\$13.00 million, US\$9.13 million) when the PSI readings increase by 100% and 500%, respectively.[24]

For electricity, the monthly household electricity consumption is given as 493.6 gWh, which is equivalent to 493,600,000 kWh, and applying the current tariff of \$0.20 per kWh for residence, we estimate the monthly increases in electricity costs incurred by Singaporean households during the one-month haze period to be S\$2.33 million (US\$1.64 million) for Scenario (1) and S\$11.67 million (US\$8.2 million) for Scenario (2) when the PSI readings increase by 100% and 500%, respectively.

[23] The calculation is based on the current tariffs in Singapore. The electricity tariff for households is \$0.20 per kWh (in effect from July 1, 2016 to September 30, 2016). The water tariffs for households are \$1.17 per cubic meter (below 40 m^3) and \$1.40 per cubic meter (above 40 m^3). An additional water conservation tax is charged for the use of water. The tax rate is 30% of the water bill when the monthly usage is under 40 cubic meters and 45% for consumption above that.

[24] The Singapore\$ to US\$ exchange rate as of October 1, 2015 was 1.4235, based on the source at finance.yahoo.com.

Based on the last five haze records, forest fires cause, on average, one month of haze-shrouded skies per year in Singapore. Moreover, the conservative, estimated externality costs, based only on utilities costs alone, are estimated to be around S$24.66 million (US$17.32 million). The Indonesian government estimates US$14 billion in economic losses related to the fires, including explicit environmental costs, health expenses, and business losses (source: the Wall Street Journal[25]). Although the externality costs on utility consumptions incurred in Singapore end up being a marginal fraction of the stated environmental costs of US$14 billion, which were incurred by Indonesia during the haze period, the additional water and electricity consumed during random and exogenous haze shocks are private goods that are purchased and consumed by households but have been ignored by households, the government, and existing studies.

8. Conclusions

Singapore's skies have been periodically covered by smoke and haze blown over by winds from the forest and peatland fires of Indonesia. The transboundary haze events impact the daily activities of Singaporean households, and their utility consumptions increase significantly during haze periods. The haze episodes have also caused significant economic losses, which include the decline in hotel room demand suffered by hoteliers in Singapore.

This paper uses multiple sources of outcome data describing utility consumption and hotel room performance, and merges them with the 24-hour PSI readings, haze-related tweets, and weather data. We find significant and positive relationships between the haze shocks and household responses in utility consumption. The results show that a 100% increase in the 24-hour PSI value is associated with a 5.1% increase in water consumption and a 2.34% increase in electricity consumption. We provide three new contributions to the current literature. First, we find robust empirical evidence of the risk-avoidance of households based on the within-the-day and between-weekday-and-weekend variations of water consumption during the haze periods. When the haze-related health risks are high, people will stay indoors after work and school on weekdays, resulting in significantly higher nighttime (6 pm to 12 am) water consumption when haze alerts are issued by the government. On weekends, when the 24-hour PSI readings reach an "unhealthy level" (>100), the daytime water consumption is not significantly different from that at nighttime, implying that people cancel their family outings during the day and stay indoors to minimize their families' exposure to the haze risks. The evidence is robust to withstand various robustness and falsification tests. When there are different haze measurements that reflect households' subjective risk perceptions and emotions, using Twitter and other weather condition status data, the results remain robust and consistent.

Second, we find that the behavioral persistency of household utility consumptions varied based on the duration of air-pollution events. In particular, water consumption rises sharply in response to air-pollution events, and households' increased water-consumption behaviors are transitory; the high consumptions revert back to the norm when the haze shock lasts for only a few days. With haze shocks that last for months, households would continue to use more electricity, even two months after the haze clears. More studies could be conducted in the future to explore the rebound effects of the behavioral responses of households to the haze risks.

[25] Source: "The numbers: Indonesia's Haze", *the Wall Street Journal*, October 27, 2015.

Third, using the daily hotel performance data from Singapore, we find significant declines in the daily occupancy rates and daily room rates during the haze periods in 2015. The declines of the hotel room demands are consistent with the risk-avoidance of foreign visitors, who shun Singapore as a tourist destination when the haze risk alerts are issued by their respective governments. These declines provide additional evidence that long-term haze shocks not only harm the personal utility costs of an individual but also lead to enormous social costs and a slowdown in economic activity.

This study aims to raise public awareness of how air-pollution affects not only our health and productivity but also every aspect of the urban quality of life. The unique, high-frequency dataset allows us to address this issue from a microperspective. This study is the first of its kind to quantify the influence of air pollution on household utility consumptions, complementing other recent works on pollution outside of the US, and the basic cost analysis provides estimates of the considerable economic costs of the haze affecting Singapore.

These estimates are particularly important in light of the dramatic increase of urban air pollution in Singapore in recent years. This paper contributes to the air-pollution literature by assessing the exogenous haze shocks that are responsible for the short-run dynamics of urban activities. The empirical analyses and findings on the air-pollution externalities on urban activities can provide valuable insights for government agencies, utility suppliers, local communities, and the hotel industry for demand forecasting when similar events occur in the future. The findings of the partial economic-welfare effects associated with increased utility consumption and decreased hotel revenue can aid government authorities and policymakers in justifying the usage of public funding in taking preventive and protective measures against transboundary haze.

Moreover, transboundary haze has been a primary concern of the ASEAN community for decades. Regional cooperation in combating the haze pollution is important to reduce the potential social and economic impacts of forest fires on source and neighboring countries. Singapore’s Parliament passed the Transboundary Haze Pollution Act in 2014, which allows the government to investigate and prosecute companies and households that are reasonably thought to have contributed to burning forests in neighboring regions and causing severe air pollution. The Coase theorem also suggests that a solution to the collective action problem could be resolved by subsidizing the party for restraining the forest burning activities that cause air pollution. Singapore has offered various financial supports and technical assistance to Indonesia to fight forest fires since 2005, and increasing these collaborations to include better fire monitoring and alerts could further help to minimize the reoccurrence of haze episodes.

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Table 1: Hourly Water Consumption and 24-Hour PSI Reading

Dependent Variable: ln(Water Consumption)	Regression (1) Full Sample	Regression (2) Full Sample	Regression (3) Sub-sample 1	Regression (4) Sub-sample 1	Regression (5) Sub-sample 2	Regression (6) Sub-sample 2
ln(24-hour PSI reading)	**0.0510*** **	**0.0289*** **	**0.0509*** **	**0.0290*** **	**0.0276** **	**0.0204**
	(0.00955)	**(0.00933)**	**(0.00954)**	**(0.00932)**	**(0.0129)**	**(0.0129)**
Constant	2.014***	1.236***	2.014***	1.235***	1.977***	1.155***
	(0.0452)	(0.0618)	(0.0452)	(0.0618)	(0.0589)	(0.0821)
Observations	4,757,132	4,757,132	4,755,055	4,755,055	1,728,745	1,728,745
R-squared	0.148	0.211	0.148	0.211	0.195	0.223
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour-period FE	No	Yes	No	Yes	No	Yes

Notes: This table shows results on the average response in hourly water consumption to the change in the hourly 24-hour PSI reading by applying Equation (1). Individual, year, month, and day of week fixed effects are included in all regressions. Column 1 presents the results of our baseline, which includes all the observations. Column 3 repeats the same analysis using a smaller sample, which drops the time periods during which both haze and "bad" weather conditions coexist. Column 5 conducts a regression analysis by further excluding the days with "bad" weather conditions, that is, we keep only the observations during normal weather conditions and haze periods. Regressions (2), (4), and (6) include additional hour fixed effects. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the household level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 2: Average Daily Household Water Consumption and Weather Status

Dependent variable:	Panel (A): Visibility		Panel (B): Haze Indicator		
	(1) Hourly	(2) Daily	(3) Hourly	(4) Hourly	(5) Daily
ln(Water Consumption)	Visibility	Visibility	Haze Status	Haze Status	Haze Indicator
Sample	Full Sample	Full Sample	Full Sample	Sub-sample 3	Full Sample
ln(Visibility)	**-0.0314****	**-0.109****			
	(0.0126)	**(0.0539)**			
ln(Temperature)	0.0266***	0.691**			0.587***
	(0.00303)	(0.312)			(0.128)
ln(Humidity)	-0.0883	0.0605			0.203
	(0.0734)	(0.160)			(0.144)
Haze Indicator			**0.0424*****	**0.0428*****	**0.210*****
			(0.0128)	**(0.0128)**	**(0.0364)**
Constant	1.574***	9.244***	1.992***	1.993***	10.80***
	(0.116)	(0.970)	(0.0544)	(0.0544)	(0.483)
Observations	3,572,190	1,053	8,537,868	8,510,342	220,224
R-squared	0.183	0.771	0.224	0.224	0.458
Year-month FE	Yes	Yes	No	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Hour FE	No	No	Yes	Yes	No
Year FE	No	No	Yes	Yes	No
Month FE	No	No	Yes	Yes	No
Household FE	Yes	Yes	Yes	Yes	Yes

Notes: Column 1 reports the relationship between visibility level and hourly water consumption. Column 5 explores the relationship between visibility level and daily aggregate water consumption. Columns 2 to 4 analyze the average response of the households' water consumption to haze episodes, which we identify as a period dummy using various measures. Column 3 reports the results estimated using the full sample, whereas Column 4 reports the results estimated using a smaller subsample, where the periods with "bad" weather conditions and visibility of 2 or below are dropped. We identify *hazeIndicator* =1 if the hourly weather status contains the keywords "light haze", "haze", or "heavy haze". Individual, year, month (or year-month), and day of week fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the household level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 3: Effect of Haze on Household Water Consumption (2012-2014)

Dependent Variable: ln(Water Consumption)

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln(Water Consumption) Testing Periods	Weekdays Full-day after 6am	Weekends Full day after 6am	Weekdays Daytime 6am to 6pm	Weekends Daytime 6am to 6pm	Weekdays Nighttime 6pm to 24am	Weekends Nighttime 6pm to 24am
ln(24-hour PSI)	0.0165	0.0350***	0.00716	0.0374***	0.0492***	0.0430***
	(0.0106)	(0.0118)	(0.0105)	(0.0119)	(0.0137)	(0.0163)
Constant	1.036***	0.806***	1.049***	0.753***	1.849***	2.084***
	(0.0731)	(0.0634)	(0.0722)	(0.0629)	(0.0669)	(0.107)
Observations	2,752,337	1,096,849	1,834,769	733,876	917,568	362,973
R-squared	0.249	0.210	0.257	0.236	0.258	0.193
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table 3 reports the estimation results using hourly water consumption and haze data from 2012 to 2014. The water consumption data between 1am and 5am are excluded in the following analysis to avoid a spurious relationship between haze measure and water usage. Columns 1 and 2 show that changes in haze level is significant and positively associated with water usage on weekends. Columns 3 and 4 present the estimates on the day-time (between 6am and 6pm) water consumption on weekdays and weekends, respectively. Columns 5 and 6 show the haze effects on night-time (6pm to 12 midnight) water consumption on weekdays and the weekends, respectively. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the household level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 4: Effect of Haze on Household Water Consumption in the Heavy Haze Period

Dependent Variable: ln(Water Consumption)

Panel A: 6am-midnight on weekdays in June 2013

Model	(1)	(2)	(3)	(4)
24-Hour PSI Cutoff	80	100	150	200
Heavy_Haze	-0.0171	-0.00827	0.00743	0.0983**
	(0.0247)	(0.0242)	(0.0293)	(0.0397)
Night	1.396***	1.397***	1.402***	1.402***
	(0.0739)	(0.0740)	(0.0738)	(0.0738)
Heavy_Haze *Night	0.0668***	0.0584***	0.0626**	0.0936*
	(0.0215)	(0.0223)	(0.0300)	(0.0522)
Constant	0.935***	0.934***	0.933***	0.934***
	(0.0551)	(0.0550)	(0.0550)	(0.0549)
Observations	138,680	138,680	138,680	138,680
R-squared	0.292	0.292	0.292	0.293
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Panel B: 6am-midnight on weekends in June 2013

Model	(5)	(6)	(7)	(8)
24-Hour PSI Cutoff	80	100	150	200
Heavy_Haze	-0.0213	-0.0381	0.00990	-0.00944
	(0.0288)	(0.0296)	(0.0333)	(0.0502)
Night	1.504***	1.506***	1.513***	1.512***
	(0.0618)	(0.0623)	(0.0624)	(0.0625)
Heavy_Haze *Night	0.0772**	0.0381	0.0342	0.0392
	(0.0338)	(0.0397)	(0.0455)	(0.0704)
Constant	0.761***	0.762***	0.756***	0.756***
	(0.0418)	(0.0418)	(0.0416)	(0.0414)
Observations	68,753	68,753	68,753	68,753
R-squared	0.251	0.251	0.251	0.251
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Notes: This table presents the estimation results on weekends and weekdays separately in Panels A and B. *Heavy_Haze* is a binary variable indicating the 24-hour PSI value above a certain level. We test four different cutoffs from 80 to 200 to explore how household water usage responds to different levels of air pollution. *Night* is a binary variable indicating the period between 5pm and midnight. The coefficient of interest is the interaction of *Haze_Haze*Night*, which measures the difference between the daytime and nighttime haze effects. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the household level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 5: Average Responses of Water Consumption (P-score Matching)

Dependent Variable: ln(Water Consumption)	(1) Full Sample Without Matching	(2) PSI=60 PSM	(7) PSI=65 PSM	(4) PSI=100 PSM	(5) PSI=150 PSM
ln(24-hour PSI)	0.0289***	0.0867**	0.121**	0.447	0.263
	(0.00933)	(0.0389)	(0.0499)	(0.829)	(2.284)
Constant	1.236***	1.786***	0.186	-0.0743	0.146
	(0.0618)	(0.609)	(1.248)	(3.392)	(7.196)
Observations	4,757,132	156,683	69,826	2,538	2,323
R-squared	0.211	0.237	0.250	0.407	0.363
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes
Hourly period FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results using the nearest neighborhood matching with replacement based on the computed propensity score. The propensity scores based on a logistic regression using a rich set of weather conditions, such as temperature, humidity, pressure, wind speed, and rain status. Then we use different sub-samples to re-run Equation (1).

Column 1 shows the results of the full-sample analysis without matching. Columns 2 to 5 show the regression results using the PSM matched samples with different treatment cutoffs. Year, month, day of the week, hourly period and household fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the individual level. *Significant at the 10 percent level; **significant at the 5 percent level; significant at the 1 percent level

Table 6: Heterogeneity Tests: Race and Dwelling Type

	Panel (A) Race			Panel (B) Dwelling Type		Panel (C) Floor Level				
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
ln(Water Consumption)	Chinese	Indian	Malay	3-room HDB	4-room HDB	Levels 1-5	Levels 6-10	Levels 11-15	Levels 16-20	Levels 21-25
ln(24-hour PSI reading)	0.0490***	0.0279	0.0778***	0.0554***	0.0432***	0.0829***	0.0290*	0.0567**	0.0396*	0.0349
	(0.0104)	(0.0580)	(0.0261)	(0.0117)	(0.0137)	(0.0176)	(0.0153)	(0.0225)	(0.0205)	(0.0244)
Constant	1.979***	2.257***	2.223***	2.047***	1.979***	1.984***	2.031***	1.915***	2.224***	2.058***
	(0.0486)	(0.2620)	(0.1490)	(0.0526)	(0.0737)	(0.0886)	(0.0874)	(0.0939)	(0.110)	(0.115)
Observations	4,065,367	180,993	455,984	2,384,273	2,361,090	888,781	1,333,329	1,478,573	633,179	411,501
R-squared	0.143	0.111	0.153	0.173	0.127	0.138	0.145	0.144	0.158	0.173
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour-period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the heterogeneous tests by race, [Chinese, Indian, and Malay], by dwelling type, [3-room HDB, 4-room HDB], and by floor level sub-samples [Levels 1-5; Levels 6-10; Levels 10-15; Levels 16-20; Levels 21-25]. Year, month, day of the week, hour-period and individual fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the household level. *Significant at the 10 percent level; **significant at the 5 percent level; significant at the 1 percent level.

Table 7: Average Daily Household Water Consumption and Social Media Responses

Independent Variable: ln(Water Consumption)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Three Topics		Topic: Haze		Topic: Environment		Topic: Health	
	Total Tweets	Tweets with Negative Emotion	Total Tweets	Tweets with Negative Emotion	Total Tweets	Tweets with Negative Emotion	Total Tweets	Tweets with Negative Emotion
Panel A: Total Number of Tweets Per Day								
ln(Number of Tweets)	0.0711***	0.0372***	0.0101*	0.0168	0.123***	0.0642***	0.0313***	0.0258**
	(0.0176)	(0.0115)	(0.00581)	(0.0140)	(0.0347)	(0.0167)	(0.00999)	(0.0120)
Constant	11.46***	11.85***	12.01***	12.17***	11.01***	11.67***	11.88***	12.06***
	(0.182)	(0.122)	(0.125)	(0.0896)	(0.329)	(0.156)	(0.110)	(0.0765)
Observations	1,096	1,073	614	272	1,096	1,036	1,076	705
R-squared	0.735	0.727	0.723	0.854	0.749	0.741	0.726	0.817
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Total Number of Likes and Reposts of Haze-related Tweets Per Day								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Number of Likes and Reposts)	0.0154	0.00990	0.00395	0.00384	0.0268***	0.0176*	0.0334***	0.0169
	(0.0149)	(0.0208)	(0.00750)	(0.0212)	(0.00680)	(0.00963)	(0.00848)	(0.0327)
Constant	12.17***	12.23***	12.27***	12.05***	12.03***	12.14***	12.05***	12.27***
	(0.0390)	(0.0418)	(0.162)	(0.213)	(0.0543)	(0.0702)	(0.0702)	(0.215)
Observations	1,045	701	227	106	1,022	606	623	213
R-squared	0.737	0.764	0.854	0.960	0.777	0.767	0.700	0.858
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The topic "haze" contains the following keywords: "haze", "hazy", "nea", "psi", "air pollution" and "singapore haze". The topic "environment" includes the following keywords: "forest", "fire", "smoke", and "burn". The topic "health" includes the following keywords: "asthma", "breath", "respiratory", "n95", and "mask". Panel A presents the relationship between the number of haze-related tweets and water consumption per day. Even columns use tweets with a negative emotion score to study the relationship between social media responses and water consumption. Columns 3 to 8 explore how tweets in each topic affect water consumption. Panel B reports the regression results using the total number of likes and reposts of haze-related tweets per day. Individual, year, month, and weekend fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the household level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 8: Average Response of Electricity Consumption to Haze Episode

Independent Variable: ln(electricity) VARIABLES	(1) PSI	(2) +temperature	(3) +rainfall	(4) +humidity	(5) +sunshine	(6) +wind
ln(PSI)	0.0550***	0.0411***	0.0409***	0.0464***	0.0275***	0.0234***
	(0.000970)	(0.00102)	(0.00102)	(0.00104)	(0.00131)	(0.00134)
ln(temperature)		0.703***	0.754***	0.918***	1.132***	1.148***
		(0.0216)	(0.0221)	(0.0247)	(0.0274)	(0.0275)
ln(rainfall)			0.00793***	-0.00176***	0.000368	-0.000905
			(0.000504)	(0.000613)	(0.000612)	(0.000615)
ln(humidity)				0.389***	0.0764***	0.0342*
				(0.0144)	(0.0177)	(0.0179)
ln(sunshine)					-0.0590***	-0.0592***
					(0.00202)	(0.00202)
ln(wind)						-0.0291***
						(0.00234)
Constant	6.097***	3.824***	3.641***	1.388***	2.216***	2.432***
	(0.00336)	(0.0703)	(0.0723)	(0.126)	(0.126)	(0.126)
Observations	469,664	469,389	469,389	469,389	469,389	469,389
R-squared	0.898	0.899	0.899	0.899	0.899	0.899
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Building FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results on the average response in monthly electricity consumption to the change in the 24-hour PSI reading by applying Equation (1) and progressively adding haze and weather measures. We include weather controls, such as monthly average temperature, total rainfall, sunshine hours, and relative humidity, in the subsequent columns. 39 weather stations (yellow circle) located in different subzones collect daily rainfall and temperature records, and 13 weather stations (black star) report wind data. The daily weather data is further aggregated into monthly frequency. Other island-wide weather measures, such as monthly average bright sunshine hours and relative humidity, are also collected We use ArcGIS to locate the weather station closest to each residential building and collect the temperature, rainfall, and wind data from the nearest weather stations. Year, month, and building fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the building level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 9: Room occupancy impact of haze outbreak in 2015
(By Class Segment)

Dependent variable: ln(occupancy)	By Class Segment					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Time lag (day)	t=6	t=5	t=4	t=3	t=2	t=1
L6.ln_PSI	-0.0143**					
	(0.00632)					
L5.ln_PSI		-0.0255***				
		(0.00620)				
L4.ln_PSI			-0.0242***			
			(0.00591)			
L3.ln_PSI				-0.0220***		
				(0.00599)		
L2.ln_PSI					-0.0146**	
					(0.00670)	
L1.ln_PSI						-0.00712
						(0.00665)
USD/SGD	0.771**	0.811***	0.804***	0.766**	0.743**	0.722**
	(0.312)	(0.310)	(0.310)	(0.310)	(0.311)	(0.312)
IDR/SGD	89.91	449.3	311.7	421.8	442.4	640.5
	(1,874)	(1,827)	(1,830)	(1,832)	(1,850)	(1,863)
CNY/SGD	-3.431**	-3.667**	-3.425**	-3.251**	-3.217**	-3.104**
	(1.549)	(1.534)	(1.529)	(1.529)	(1.539)	(1.544)
INR/SGD	17.88	17.51	16.91	16.40	15.16	14.74
	(11.07)	(10.85)	(10.84)	(10.85)	(10.90)	(10.99)
ln_STI	0.337**	0.302**	0.322**	0.328**	0.332**	0.328**
	(0.133)	(0.133)	(0.132)	(0.133)	(0.133)	(0.133)
Constant	-1.458	-1.077	-1.283	-1.303	-1.317	-1.378
	(1.096)	(1.093)	(1.091)	(1.092)	(1.097)	(1.099)
Year-month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Hotel region FE	YES	YES	YES	YES	YES	YES
Observations	992	992	992	992	992	992
R-squared	0.381	0.388	0.388	0.386	0.381	0.378

Notes: The dependent variable is the hotel room occupancy rate (daily index) in logarithm term across different hotel class submarket (luxury, upper upscale, and upscale). Current and lagged value of 24-hour PSI index in logarithm term are the explanatory variables to examine the effect of haze one week ago on hotel performance. The coefficient on PSIt=0 stays statistically insignificant and is not included in the table. Singapore Straits Times Index (STI) in natural logarithm form and currency exchange rates with Indonesian rupiah (IDR), Chinese Yuan Renminbi (CNY), Indian Rupee (INR), and the United States Dollar (USD) being compared to the Singapore dollar (SGD) are included in the regression. Month-year fixed effects and day of the week fixed effects are included to account for the variations of hotel performance indices over time. Standard errors are reported in parentheses under the coefficient estimates. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 10: Room occupancy impact of haze outbreak in 2015
(By Geographic Area)

Dependent variable: ln(occupancy)	By Geographic Area					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Time lag (day)	T=-6	T=-5	T=-4	T=-3	T=-2	T=-1
L6.ln_PSI	-0.0190***					
	(0.00551)					
L5.ln_PSI		-0.0329***				
		(0.00537)				
L4.ln_PSI			-0.0310***			
			(0.00512)			
L3.ln_PSI				-0.0272***		
				(0.00520)		
L2.ln_PSI					-0.0215***	
					(0.00583)	
L1.ln_PSI						-0.0119**
						(0.00581)
USD/SGD	0.968***	1.016***	1.007***	0.955***	0.935***	0.908***
	(0.272)	(0.268)	(0.268)	(0.269)	(0.271)	(0.272)
IDR/SGD	-270.5	230.5	55.83	220.3	125.3	348.8
	(1,634)	(1,582)	(1,585)	(1,591)	(1,611)	(1,627)
CNY/SGD	-3.838***	-4.120***	-3.807***	-3.569***	-3.592***	-3.461**
	(1.350)	(1.328)	(1.324)	(1.328)	(1.340)	(1.349)
INR/SGD	16.31*	15.62*	14.84	14.05	12.98	12.72
	(9.646)	(9.392)	(9.384)	(9.425)	(9.495)	(9.600)
ln_STI	0.387***	0.341***	0.368***	0.375***	0.380***	0.374***
	(0.116)	(0.115)	(0.115)	(0.115)	(0.116)	(0.117)
Constant	-1.969**	-1.497	-1.756*	-1.792*	-1.791*	-1.863*
	(0.956)	(0.946)	(0.944)	(0.949)	(0.956)	(0.960)
Year-month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Hotel type FE	YES	YES	YES	YES	YES	YES
Observations	992	992	992	992	992	992
R-squared	0.339	0.356	0.356	0.350	0.341	0.334

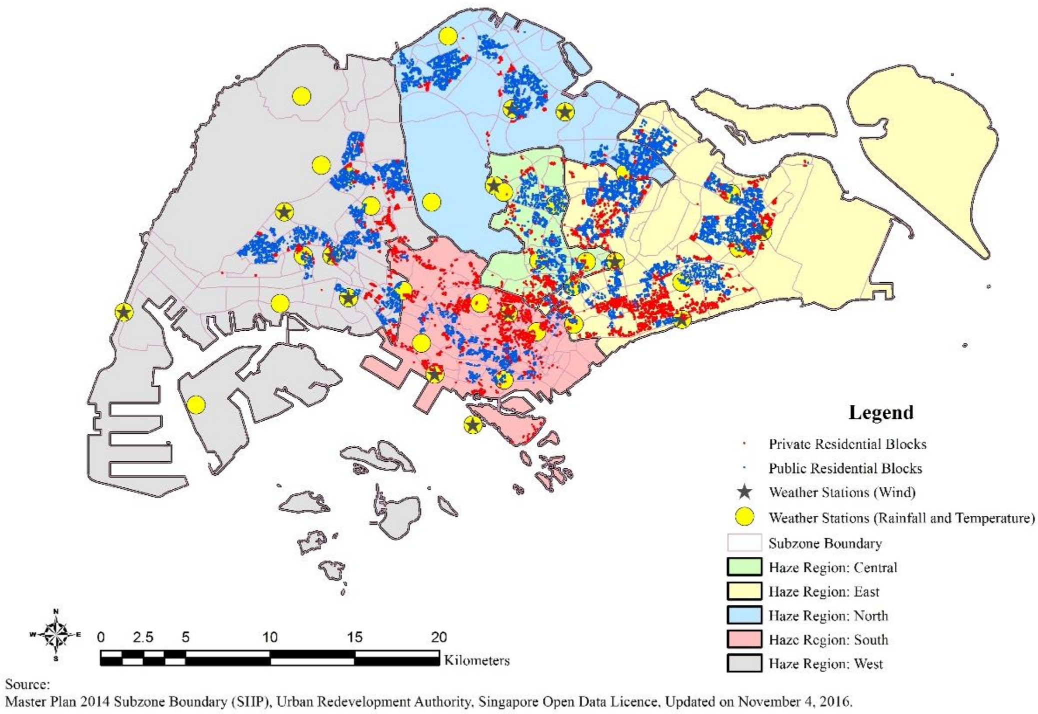
Notes: The dependent variable is the hotel room occupancy rate (daily index) in logarithm term across different geographic regions(Marina Bay, Sentosa, Orchard, and River Valley). Current and lagged value of 24-hour PSI index in logarithm term are the explanatory variables to examine the effect of haze one week ago on hotel performance. The coefficient on PSIt=0 stays statistically insignificant and is not included in the table. Singapore Straits Times Index (STI) in natural logarithm form and currency exchange rates with Indonesian rupiah (IDR), Chinese Yuan Renminbi (CNY), Indian Rupee (INR), and the United States Dollar (USD) being compared to the Singapore dollar (SGD) are included in the regression. Month-year fixed effects and day of the week fixed effects are included to account for the variations of hotel performance indices over time. Standard errors are reported in parentheses under the coefficient estimates. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 11: Room Price Impact of Haze Outbreak in 2015

Dependent variable: ln(price)	Panel A: By Class Segment		Panel B: Geographic Area	
Model	(1)	(2)	(3)	(4)
Time lag (day)	t=0	t=-1	t=0	t=-1
ln_PSI	-0.0199***		-0.0182***	
	(0.00444)		(0.00591)	
L1.ln_PSI		-0.0154***		-0.0131**
		(0.00463)		(0.00615)
USD/SGD	0.968***	0.976***	0.943***	0.948***
	(0.216)	(0.217)	(0.287)	(0.288)
IDR/SGD	-2,575**	-2,072	-4,769***	-4,264**
	(1,302)	(1,297)	(1,732)	(1,722)
CNY/SGD	-5.474***	-5.266***	-4.229***	-4.017***
	(1.073)	(1.076)	(1.427)	(1.428)
INR/SGD	1.639	-1.603	6.035	2.846
	(7.698)	(7.657)	(10.24)	(10.16)
ln_STI	0.398***	0.400***	0.388***	0.390***
	(0.0925)	(0.0930)	(0.123)	(0.123)
Constant	-0.562	-0.640	-0.508	-0.593
	(0.763)	(0.765)	(1.015)	(1.016)
Year-month FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Hotel type FE	YES	YES	No	No
Hotel region FE	No	No	YES	YES
Observations	992	992	992	992
R-squared	0.916	0.915	0.816	0.815

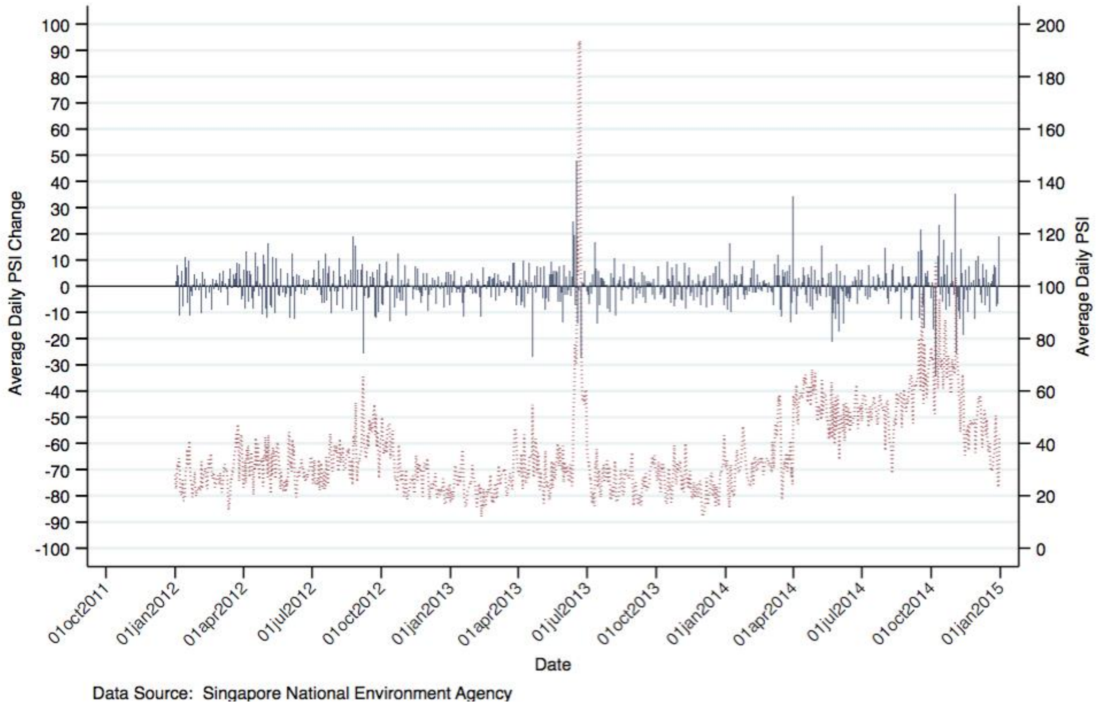
Notes: The dependent variable is the hotel room price (daily index) in logarithm term. Panel A shows the effects of haze on daily hotel room rates estimated for each hotel class submarket (luxury, upper upscale, and upscale). Panel B presents the haze impact on daily room across different geographic regions(Marina Bay, Sentosa, Orchard, and River Valley). Singapore Straits Times Index (STI) in natural logarithm form and currency exchange rates with Indonesian rupiah (IDR), Chinese Yuan Renminbi (CNY), Indian Rupee (INR), and the United States Dollar (USD) being compared to the Singapore dollar (SGD) are included in the regression. Month-year fixed effects and day of the week fixed effects are included to account for the variations of hotel performance indices over time. Standard errors are reported in parentheses under the coefficient estimates. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Figure 1: Singapore Residential Housing Location, Weather Stations and Air Quality Reporting Regions



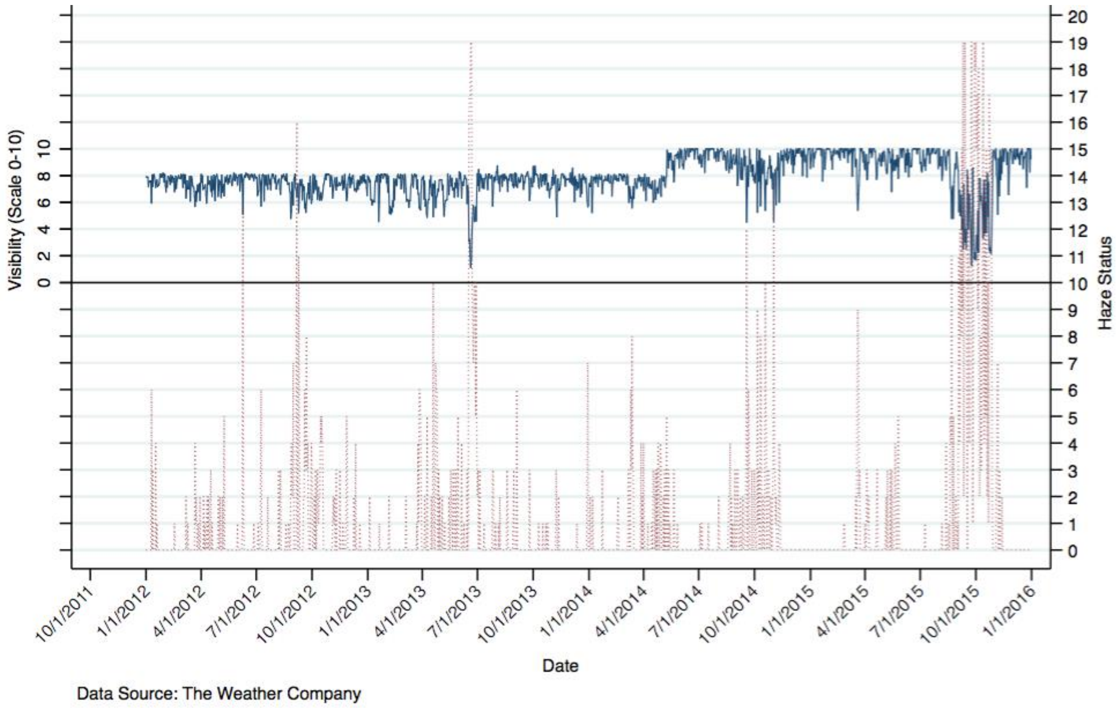
Notes: The panel data contains monthly aggregated electricity records for 4,200 private residential buildings and 9,336 public residential buildings from Jan 2013 to Dec 2015. The GIS map shows the geographical distribution of residential housing in the sample. Residential properties are randomly distributed among the five NEA air quality-reporting regions (north, south, east, west, and central Singapore). Geographic boundary of the five haze-reporting regions, Masterplan subzone boundaries, 39 weather stations (yellow circle) collected daily rainfall and temperature records, and 13 weather stations (black star) reported wind data.

Figure 2: Average Daily 24-Hour PSI Value from January 1, 2012, to December 31, 2014



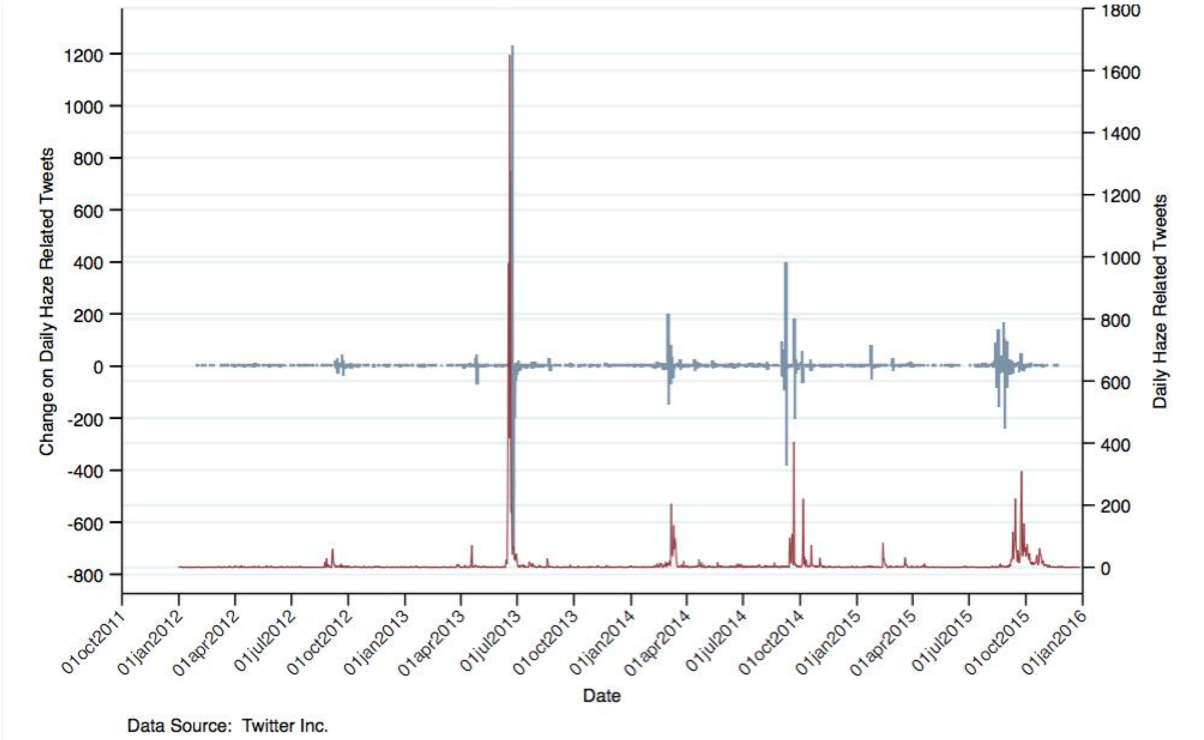
Notes: This figure plots the 24-hour PSI readings from January 2012 to December 2015. The red line represents the variation of average daily 24-hour PSI readings and the blue line stands for the day-to-day changes of the average daily PSI measure.

Figure 3: Daily Haze Status and Visibility Measure from January 2012 to December 2015



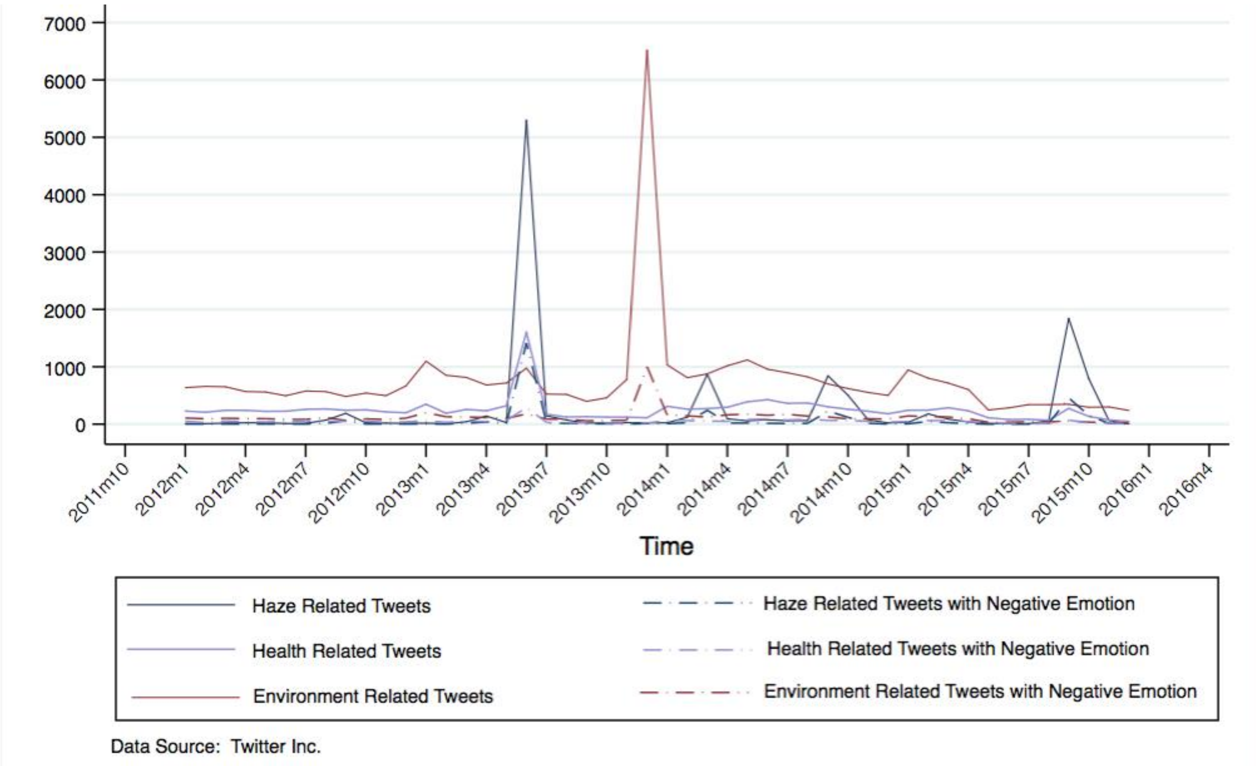
Notes: This figure presents the daily visibility level and haze status from 2012 to 2015. The blue line stands for the visibility measure, which ranges from 0 to 10, where 0 indicates no visibility and 10 indicates very clear visibility. The red line represents the number of counts per day with "haze" as the weather status reported by The Weather Channel.

Figure 4: Daily Haze-related Tweets from January 1, 2012 to December 31, 2015



Notes: This figure shows the daily haze-related tweets generated by Singapore users during the major haze episodes in the study periods. The red line represents the daily counts of haze-related tweets, and the blue line represents the day-to-day change in daily counts.

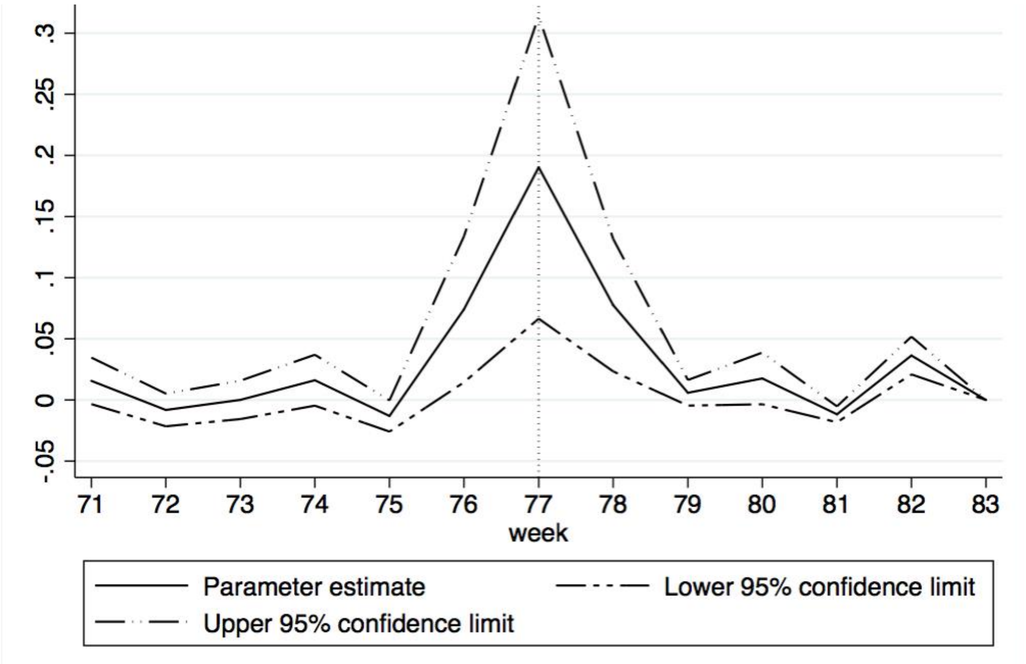
Figure 5: Monthly Haze-related Tweets from January 2012 to December 2015



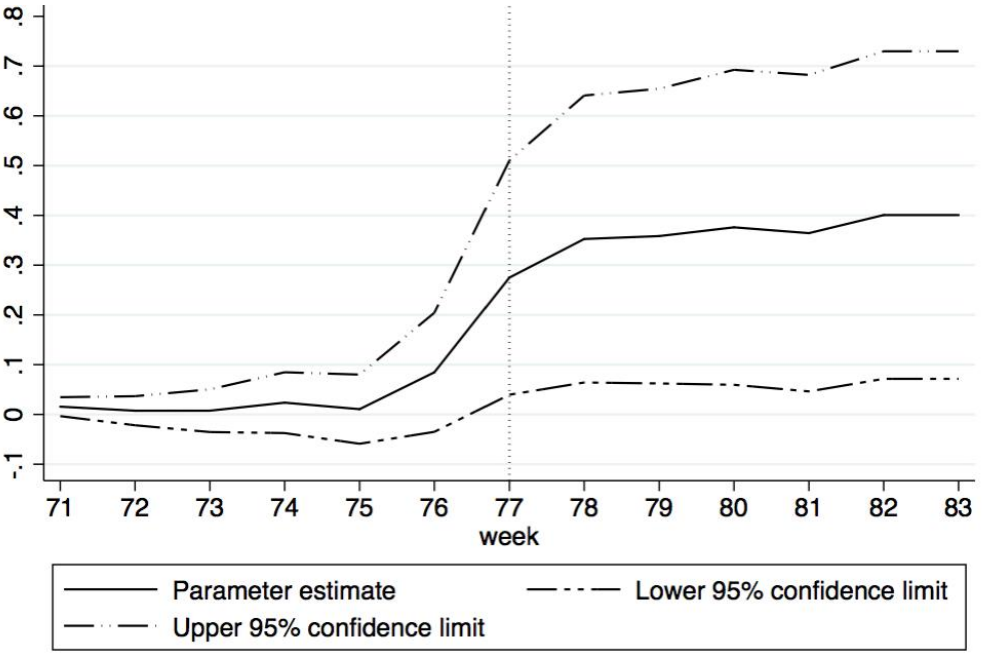
Notes: We categorize the Twitter data into three topics: haze, environment, and health. This figure shows the trends of the three topics from 2012 to 2015. Solid lines represent the monthly tweet counts of each topic, and dashed lines represent tweets with negative emotion. The topic "haze" contains the following keywords: "haze", "hazy", "nea", "psi", "air pollution", and "singapore haze". The topic "environment" includes the following keywords: "forest", "fire", "smoke", and "burn". The topic "health" includes the following keywords: "asthma", "breath", "respiratory", "n95", and "mask".

Figure 6: Short-term Haze Episodes and Estimated Water Consumption Responses

Panel A. Dynamic Water Consumption Response to Haze Episodes in Mid-June 2013

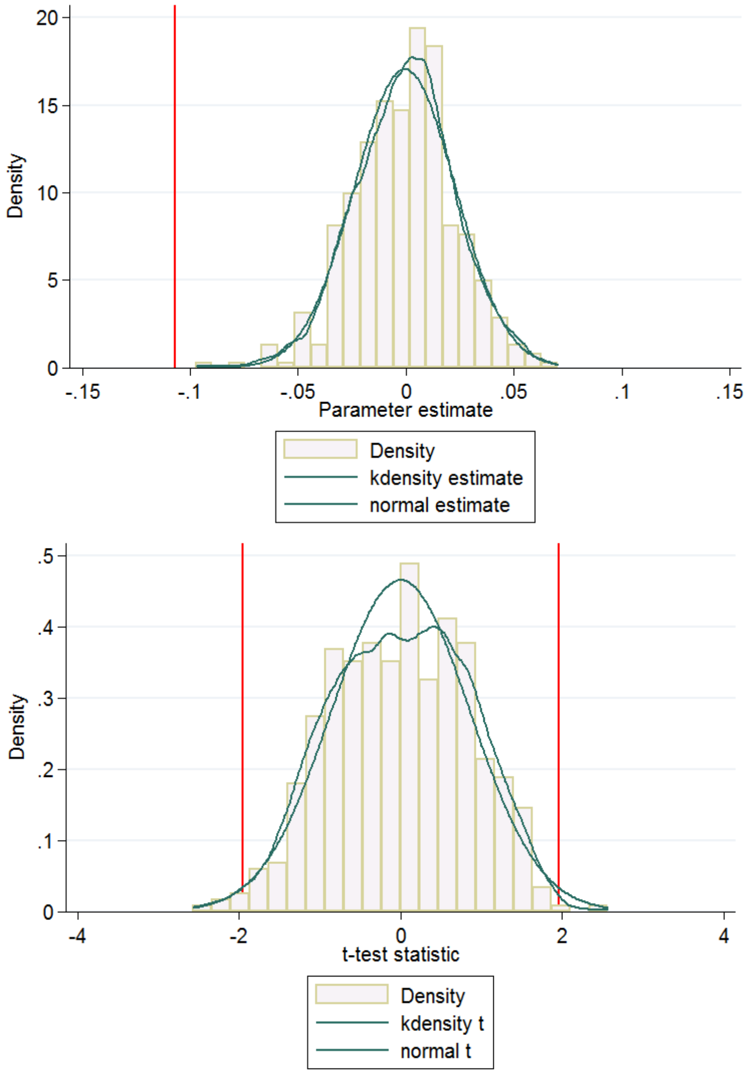


Panel B. Cumulative Water Consumption Response to Haze Episodes in Mid-June 2013



Notes: These figures plot the weekly water consumption trend. The one-week-long haze period occurring in the third week of June 2013 is identified by week "77," whereas other numbers correspond to the 13-week window before and after June 2013 (week 77). Panel A graphs the impact of the one-week air pollution event over time. Panel B graphs the entire path of the cumulative coefficients β_{a+b}. The dashed lines represent the corresponding 95% confidence intervals.

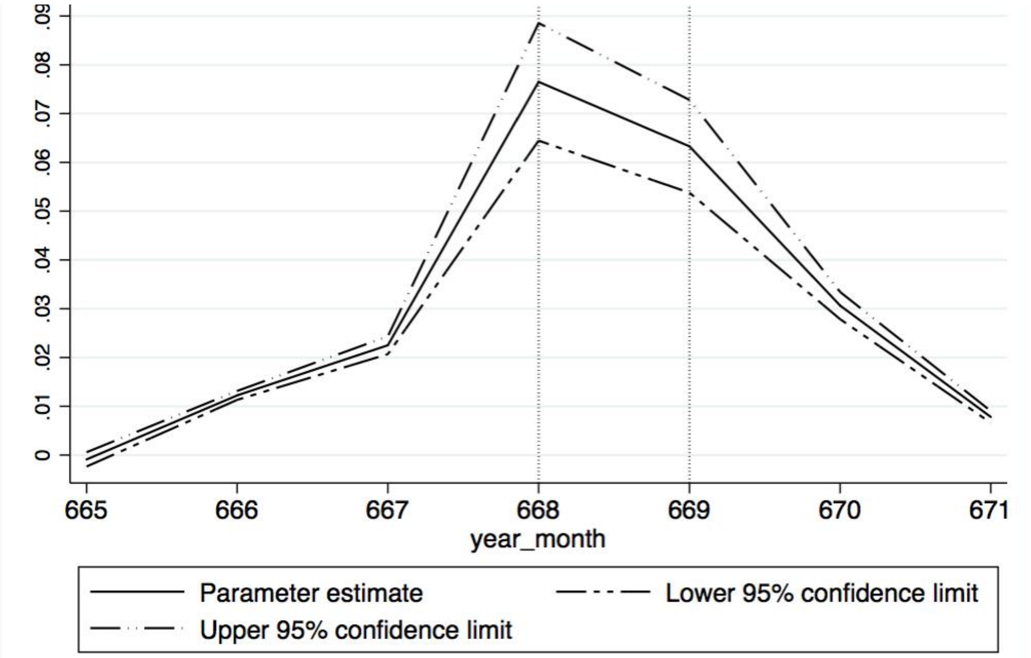
Figure 7: Distribution of the Parameter Estimates and T-statistics with the Random Assignment of Hazy Days



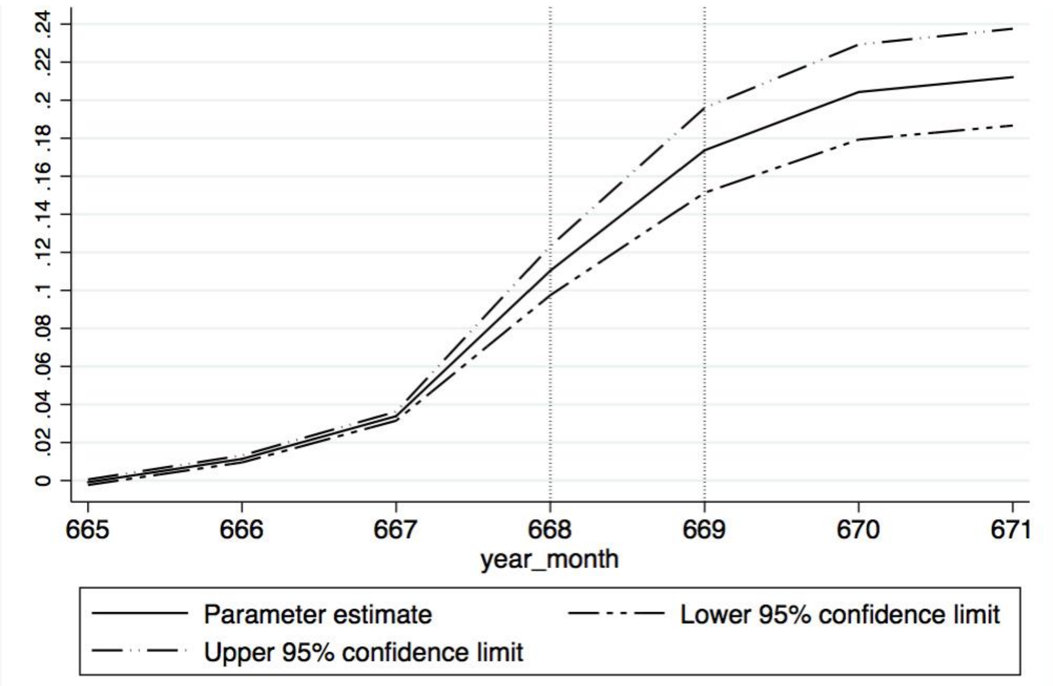
Notes: These figures show the distribution of parameter estimates and T-statistic of falsification tests by randomly assigning 30 "placebo" hazy days in each year for the three consecutive years, and repeat the randomization process over 500 times. The top panel of Figure 7 presents the distributions of the estimated parameters with random assignment, whereas the lower panel shows the t-statistics of the falsification tests.

Figure 8: Long-term Haze Episodes and Estimated Electricity Consumption Responses

Panel A. Dynamic Electricity Consumption Response to Haze Episodes in Sept and Oct 2015



Panel B. Cumulative Electricity Consumption Response to Haze Episodes in Sept and Oct 2015



Notes: This figure plots the dynamic response of electricity consumption to the two-month long haze shock, for a seven-month window. Panel A graphs the dynamic monthly electricity consumption, and Panel B shows the month-to-month cumulative responses of experiencing such long-term haze episodes. The dashed lines represent the corresponding 95% confidence intervals. The two months with the haze shocks are coded using the year-month variable with the corresponding numbers of "668" (September 2015) and "669" (October 2015).

Appendix

Table A1: Weather Conditions Summary Statistics for P-score Matching

Panel A. Weather conditions of the treatment and control groups (before matching)

Two-sample T Test with Equal Variances

	Control Group		Treatment Group		
Variables	Observations	Mean	Observations	Mean	Mean Diff
Temperature	3319151	28.475	265444	29.646	-1.171***
Humidity	3319151	0.762	265444	0.7	0.061***
Visibility	3309470	7.447	264020	7.087	0.360***
Pressure	3319151	578.702	265444	846.399	-267.697***
Wind Speed	3271963	8.735	258975	9.315	-0.580***
Rain Status	7807358	0.115	731498	0.055	0.060***

Panel B. Weather conditions of the treatment and control groups (after matching)

Two-sample T Test with Equal Variances

	Control Group		Treatment Group		
Variables	Observations	Mean	Observations	Mean	Mean Diff
Temperature	1036	29.356	256006	29.713	-0.357***
Humidity	1036	0.719	256006	0.696	0.023***
Visibility	1036	7.638	256006	7.116	0.523***
Pressure	1036	841.106	256006	846.06	-4.954
Wind Speed	1036	9.53	256006	9.321	0.209
Rain Status	1036	0.198	256006	0.156	0.042***

Notes: We perform nearest neighbor matching with replacement based on the computed propensity score to pair the treatment and control samples. This table reports the summary statistics of the treatment and control samples, both before and after the nearest neighborhood propensity score matching. The treatment sample consists of hourly periods with 24-hour PSI readings over 60 from 2012 to 2014. The PSM significantly reduces the post-matching differences between the treatment and control periods in all observable weather conditions.

Table A2: Electricity Consumption and Emotional Changes Expressed by Twitter Users

Dependent Variable: ln(Electricity Consumption)	ln(Average Negative Emotion)
ln(-Average Negative Emotion Score)	**0.122*** **
	(0.00609)
Constant	6.383***
	(0.00647)
Observations	237,144
R-squared	0.842
Building FE	Yes
Year FE	Yes
Month FE	Yes

Notes: This table presents the results of estimating Equation (1) using the emotion score as an independent variable. We analyze the contents of each tweet using sentiment analysis techniques and give each tweet an emotion score, which ranges from -1 to 1. We include tweets with negative scores in the analysis and take the absolute value of the negative score. Year, month, and building fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the building level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table A3: Heterogeneity in Housing Price/Sq. m.

Dependent Variable: ln(Electricity Consumption)	(1) Below $10,000	(2) Between $10,000 and $20,000	(3) Between $20,000 and $30,000	(4) Above $30,000
ln(meanPSI)	0.0903***	0.0877***	0.0603*	0.0428
	(0.00975)	(0.00763)	(0.0339)	(0.104)
ln(AirTemperatureMax)	0.0430	-0.194***	-0.383	0.572
	(0.0890)	(0.0664)	(0.236)	(0.716)
ln(TotalRainfallMillimetre)	-0.00994***	-0.00669**	-0.0283***	-0.0147
	(0.00336)	(0.00276)	(0.00968)	(0.0235)
ln(BrightSunshineDailyMeanHour)	-0.0494***	-0.0178	-0.0640	-0.0333
	(0.0173)	(0.0134)	(0.0559)	(0.129)
ln(HoursMeanRelativeHumidity)	0.542***	0.438***	0.636	0.672
	(0.136)	(0.122)	(0.526)	(1.453)
Constant	3.430***	4.618***	4.921*	1.685
	(0.681)	(0.635)	(2.686)	(7.998)
Observations	44,191	86,355	9,105	1,348
R-squared	0.768	0.761	0.789	0.800
Public Housing Dummy	0.768	0.761	0.789	0.800
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Building FE	Yes	Yes	Yes	Yes

Notes: This table provides the results of a heterogeneous test that show how the effects of exogenous air pollution events vary with different levels of housing prices. Private housing prices are collected from REALIS (Real Estate Information System), and HDB prices are collected from Singapore Statistics. We use the last housing transaction that was recorded in the period from 2013 to 2015 to proximate the housing value. Year, month, and building fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the building level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table A4: Heterogeneity in Dwelling Type

Dependent Variable: ln(electricity) Sub-sample	(1) 1 or 2-room HDB	(2) 3-room HDB	(3) 4-room HDB	(4) 5 or executive room HDB	(5) whole HDB building
ln(PSI)	-0.00113	0.0254***	0.0261***	0.0248***	0.0244***
	(0.0104)	(0.00274)	(0.00140)	(0.00137)	(0.00156)
ln(temperature)	1.334***	1.249***	1.177***	1.143***	1.245***
	(0.180)	(0.0562)	(0.0286)	(0.0281)	(0.0317)
ln(rainfall)	-0.0111***	-0.00236*	-0.00302***	-0.00179***	-0.00205***
	(0.00405)	(0.00134)	(0.000668)	(0.000645)	(0.000764)
ln(humidity)	0.0823	0.157***	0.0598***	0.0106	0.0456**
	(0.152)	(0.0397)	(0.0194)	(0.0179)	(0.0218)
ln(sunshine)	-0.0680***	-0.0609***	-0.0616***	-0.0614***	-0.0601***
	(0.0140)	(0.00401)	(0.00208)	(0.00206)	(0.00241)
ln(wind)	0.00458	-0.00504	-0.0369***	-0.0467***	-0.0388***
	(0.0142)	(0.00493)	(0.00271)	(0.00282)	(0.00287)
Constant	0.313	0.736***	1.804***	2.371***	2.071***
	(0.958)	(0.280)	(0.137)	(0.127)	(0.153)
Observations	15,824	89,300	217,782	194,542	318,549
R-squared	0.650	0.662	0.703	0.750	0.913
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Building FE	Yes	Yes	Yes	Yes	Yes

Notes: This table provides the results of a heterogeneous test that show how the effects of exogenous air pollution events vary with different dwelling types of HDB flats. Year, month, and building fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the building level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table A5: Cross-domain Elasticity

ln(total water)	(1)
VARIABLES	Elasticity
ln(building_electricity)	**0.542****
	0.00862
ln(medPSI)	(0.123)
	-0.563
ln(AirTemperatureMax)	(0.423)
	0.00472
ln(TotalRainfallMillimetre)	(0.0182)
	-0.257
ln(BrightSunshineDailyMeanHour)	(0.217)
	-1.917**
ln(HoursMeanRelativeHumidity)	(0.777)
	0.00862
Constant	(0.123)
	-0.563
Observations	192
R-squared	0.904
Year FE	Yes
Month FE	Yes
Building FE	Yes

Notes: We construct a subsample of nine HDB building records between January 2013 and December 2014 by merging monthly water consumption data with electricity consumption data. This table presents the cross-domain elasticity by regressing monthly electricity on total water consumption at the building level. Year, month, and building fixed effects are included in all regressions. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the building level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table A6: Sample Construction of Hotel Room Rates and Occupancy Indices

Panel A: Room rates and occupancy aggregated at class segment – day level

Class Segment	**Population 1 (Total Rooms)**	**Sample 1 (Total Rooms)**	**Sampling Fraction**
Luxury	11,428	9,543	83.5%
Upper Upscale	17,261	15,022	87.0%
Upscale	14,890	8,907	59.8%
Total	**43,579**	**33,472**	**76.8%**

Panel B: Room rates and occupancy aggregated at geographic region – day level

Central Region	**Population 2** (Total rooms)	**Sample 2** (Total Rooms)	**Sampling Fraction**
Marina Bay	17,098	12,749	74.6%
Sentosa	3,324	2,293	69.0%
Orchard	13,347	10,507	78.7%
River Valley	8,462	5,274	62.3%
Total	**42,231**	**30,823**	**73.0%**

Notes: This table illustrates the market-wide room prices index and the occupancy index of two datasets used in the empirical analysis. Panel A presents the daily level room rates and occupancy level categorized by hotel class. Panel B shows the daily hotel performance by geographic area.