The Impact of Transboundary Haze Pollution on Household Utilities Consumption

Sumit Agarwal [†]
Tien Foo Sing[‡]
Yang Yang[§]

This version: November 17, 2019[¶]

[†] Department of Finance and Department of Real Estate, National University of Singapore, 15 Kent Ridge Drive, Singapore 119245 (email: ushakri@yahoo.com).

[‡] Department of Real Estate, School of Design Environment, National University of Singapore, 4 Architecture Drive, Singapore 117566. (email: rststf@nus.edu.sg).

[§] CUHK Business School, The Chinese University of Hong Kong, 12 Chak Cheung Street, Shatin, N.T. Hong Kong SAR (email: zoeyangyang@gmail.com).

[¶] 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 are grateful for comments and suggestions from Joseph Shapiro, Tsur Somerville, Daniel McMillen, Yuming Fu, Henk Folmer, and seminar participants in the 2018 AREUEA-ASSA Conference, the 2017 Meetings of the Regional Science Association International Conference, and the "Asian Green Cities" Workshop in Tsinghua University, Syracuse University, and Baruch College at CUNY.

The Impact of Transboundary Haze Pollution on Household Utilities Consumption

Abstract

This paper examines the causal effects of air pollution on the household consumption of water and electricity in Singapore. Using the transboundary haze pollution caused by forest fires in Indonesia as an exogenous shock, we find that increases in haze pollutant intensity in the air significantly increase water and electricity consumption. In particular, the intra-day and inter-day analyses on hourly household water consumption are consistent with the risk avoidance and the risk mitigation behaviors during severe haze episodes. During the haze periods, households stay indoors and avoid outdoor activities to minimize exposure to health risks. When they need to engage in outdoor activities during the weekdays, they increase efforts in mitigating health risks associated with air pollution. Moreover, the analysis of social media data shows that the level of public awareness of air pollution is positively related to energy consumption by households. In addition, the effects of haze-induced utilities consumption is correlated with the duration of air pollution. While household utilities consumption quickly returns to normal after transitory pollution exposure, the effects are stronger and persistent after a longer period of air pollution; households maintain a higher level of utilities consumption for two months after a lengthy haze, suggesting a substantial spending on additional water and electricity usage due to air pollution events.

Keywords: Transboundary air pollution, haze, environmental externalities, avoidance behavior, risk mitigation, economic activities, household utilities consumption

JEL Code: D12, F62, Q40, Q53, Q54

1 Introduction

The idea that air pollution substantially influences economic outcomes has received considerable attention from economists in the last decade. In a wide variety of contexts, the empirical literature has focused almost exclusively on the direct effects and explicit costs (e.g., health outcomes, labor productivity, and consumption behaviors) of air pollution, leaving the resources used during pollution events, such as water and electricity, largely unmeasured. Since potential climatic variables have long been essential for the design of utilities systems, it is also critical to consider utilities consumption in the context of air pollution. The US Global Change Research Act of 1990 highlights the concern about climate change. Research shows that climate change increases energy consumption. As estimated in Mansur et al. (2008), a 5C warming increases energy expenditure by \$57 billion per year in the US, of which 62% of the impact is in the residential sector.

An understanding of the impacts of air pollution would help to identify the consequences of electricity consumption behaviors and the potential feedback loops, where electricity demand influences greenhouse gas emissions, which in turn affects future electricity demand. The scarcity of water resources and consequent limited supply of water has growing implications for rapidly increasing city populations, such that local governments now promote water conservation. Thus, a greater understanding of the relationship between air pollution and water consumption could contribute to the forecasting of future water consumption and thereby enable managers of water supply to plan for demands in a changing environment. This paper is the first to rigorously assess the causal effects of air pollution on household utilities consumption.

Estimating the causal relationship between air pollution and energy consumption is difficult for several reasons. First, identifying clean causal effects of air pollution and energy consumption is challenging as everyday energy consumption affects pollutant levels and, at the same time, pollutants and climate factors affect the demand for energy. Existing literature focuses on the impact of energy consumption on air pollution and suffers from potential reserve causality issues. Second, it is difficult to disentangle the endogenous relationships between air pollution and human activities, which are highly correlated with coincident weather conditions, seasonal trends, and local economic activities. Third, exposure to pollution levels is typically endogenous. Even if ambient pollution were exogenous, individuals may respond to ambient levels by reducing time spent outside (Neidell, 2009), which would in turn affect the demand. While high frequency, micro-level energy consumption data would help to understand individual consumption patterns, the scarcity of such data presents a perennial challenge.

In this paper, we employ unique panel datasets of high frequency, micro-level utilities consumption and use the haze crises of Indonesia as *random* and *exogenous* shocks to analyze the direct impact of haze shocks on the utilities consumption of households in the neighboring country. The haze episodes that have occurred in Singapore provide a unique opportunity[1] to study the issue at hand. First, the haze episode in Singapore is purely *random* and *exogenous* because the air pollutants originate from Indonesia and depend on wind direction (Sheldon and Sankaran, 2017). Moreover, as Singapore is a small island spanning only 709 square kilometers, air pollution is homogeneously spread island-wide, which means everyone in Singapore is exposed to the air pollutants, especially when the Pollutants Standards Index (PSI) reading is over 300[2]. Therefore, the potential endogeneity bias associated with local economic activities (Moretti and Neidell, 2011) and sorting by residents (Dominici et al., 2014; Chay and Greenstone, 2003a,b, 2005) and firms (Greenstone, 2002) in existing studies is unlikely to be a concern in assessing the causal effects of air pollution on household utilities consumption. Furthermore, our method of identifying air pollution directly by hourly measurement of pollution flotation in the areas concerned could significantly reduce possible measurement error.

Recent studies have looked into the temporary exogenous changes in climate outcomes over time within a specific spatial area and they have found that these weather patterns can causatively identify the outcomes of weather changes on various economic outcomes (Dell et al., 2014). By exploiting the high frequency fluctuations in ambient air quality in Singapore, we test whether the haze shocks significantly influence energy consumption and investigate the underlying mechanisms by which different levels of air pollution and duration of exposure affect consumption behavior. We further strengthen the causal relationship of transboundary haze pollution on energy consumption by using a two stage least square approach and employ the satellite fire data to instrument for the air pollution in Singapore.

There are three key findings from our analyses. First, based on the unique datasets provided by the Singapore Public Utilities Board (PUB) and the Energy Market Authority (EMA), which contains detailed information of the hourly water consumption of 376 house-

---

[1] We use the transboundary hazes in Singapore caused by the forest fires in Indonesia as the exogenous shock in our natural experimental design. In Singapore, most of the pollution from oil refineries and petrochemicals is confined to Jurong Island, a reclaimed island to the west of the main island. A set of stringent industrial emission standards and guidelines has 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 put in place by the government to create a sustainable living environment that is clear of industrial pollution. Therefore, Singapore offers an ideal environment to identify the effects of air pollution in our natural experiment. After all, the transboundary haze shock is random and exogenous, as the shocks are caused solely by the forest fires on the neighboring Indonesian islands. The high concentration of PM2.5 pollutants in Singapore's skies is independent of the local industries activities.

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

holds from January 1, 2012 to December 31, 2014, and the monthly electricity consumption for all the public and private residential buildings (based on 15,315 unique postal codes[3]) in Singapore from January 2013 to December 2016, we find that Indonesia's Fire Radiative Power (FRP) is statistically significant determinant of PSI readings in Singapore, and a 100% increase in the predicted hourly 24-hour PSI reading is associated with an average water and electricity consumption increase of 14.3% and 7.9%, respectively. The results remain robust after using alternative pollution measures and controlling for various confounding factors, such as weather conditions and on-peak and off-peak consumption. In addition, we collect detailed data from a social media website (Twitter) to study the awareness and sentiment responses[4] of households during the haze periods and their effects on household utilities consumption. Our findings affirm that the negative sentiment related to haze could significantly predict increases in utilities consumption and we show that public consciousness of haze conditions explains 17.7% to 23.6% of the haze effects, suggesting the potential mechanism of haze pollution affect utilities consumption.

Second, our analysis of the intraday (daytime versus nighttime) and interday (weekday versus weekend) variations of household water consumption in response to air pollution suggests that the significant increases in utilities consumption can be explained by the households' risk avoidance and risk mitigation behaviors. The elevated nighttime water consumption levels reflect the households' substantial risk mitigation behaviors (e.g., consuming more water and electricity after outdoor activities when following government advisories). The households also reduced their exposure to air pollution risks by staying indoors (e.g., avoiding family outings on the weekend during severe haze episodes). In particular, the risk avoidance behaviors varied based on the severity of the haze episodes.

Moreover, our dynamic analysis of the short- and long-term effects of air pollution reveals significant differences in the persistence of increased utilities consumption. While the households reverted to their original consumption behaviors one week after a short-term haze shock, the consumption levels remained high for two months after a long-term haze episode. This could indicate the long term effects on people's health causing them to continue their usage of appliances such as air conditioners and purifiers to maintain a healthier home environment. However, it could also indicate the adoption of wasteful habits that increase carbon emissions and add to the stress on the environment and society.

Our findings also provide important policy implications for the continued development of energy and environmental regulations across the globe. The increase in wildfires in western US and Canada (Kasischke and Turetsky, 2006; Dennison et al., 2014; Abatzoglou and

---

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

[4] 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.

Williams, 2016) have resulted in the loss of billions of dollars and affected the lives of thousands. Many developing countries in Asia have implemented intervention strategies to mitigate the effects of air pollution. For example, the agreement on transboundary haze pollution, which was signed by ASEAN Member States in 2002, was established to prevent and mitigate forest fires. In addition, China introduced the Huai River heating policy and a national cap-and-trade program on carbon emissions in 2017. In this study, we calculate the estimated economic costs of additional utilities consumption associated with the transboundary haze in Singapore. Following the traditional method of assessing environmental externalities and providing a lower bound of the estimated costs of these environmental externalities (Currie and Neidell, 2005; Bento et al., 2015; Chang et al., 2016), the back-of-the-envelope estimations show that, Singaporean household water spending increases by \$74.11 million (\$61.75 per household), and electricity spending increases by \$20.13 million (\$16.78per household) per year when a heavy-haze shock occurs[5]. Therefore, the implications for government policy related to mitigation and prevention of haze and forest fires are important.

This paper makes three contributions to environmental and energy literature. First, this is one of the first attempts to identify how air pollution causally affect household energy consumption. Unlike the earlier studies that use local or regional sources of pollution emissions as exogenous shocks, the haze used in our special setting was emitted by Indonesian forest fires and traveled across the country's border to Singapore, creating a clean and exogenous shock, which overcomes the challenges in identifying causative effects of air pollution on energy demand as reverse causation is not likely to be a major concern. 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 air pollution on energy consumption during the tests.

Second, the study helps to understand the specific mechanisms through which bad air quality leads to increased water and electricity demand. By exploiting high-frequency changes in pollutants and utilities consumption at household and building level, we present new evidence of humans' risk avoidance and mitigation behaviors in response to the air pollution using within-the-day (daytime and nighttime) and between-the-day (weekday and weekend) variations of their utilities consumption. Moreover, the study resolves the issue of whether and how the effect of long-run fluctuations (a two-month long haze shock) in air quality differ from the results of short-run changes (a one-week long haze episode).

Third, this paper extends the existing literature by addressing the issue of air pollution in Southeast Asia. We find significant evidence of cross-border air-pollution effects on daily human activities in Southeast Asia, which can contribute to air pollution studies outside

---

[5] The results show that 10% reduction in the number of extreme pollution days in Singapore would generate a total water and electricity savings of approximately S\$94.24 million (US\$66.21million).

North America. 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 (Sheldon and Sankaran, 2017; Rosales-Rueda and Triyana, 2018).

The remainder of this paper is as follows. Section 2 reviews the related empirical literature on air pollution and energy consumption. 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 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 and risk mitigation behavior. Section 6 presents the main empirical results, which include those from the robustness, falsification and heterogeneity tests. A general estimation of the welfare costs associated with the transboundary air pollution is included in Section 7. Finally, Section 8 concludes the study.

2 Related Studies on Air Pollution and Energy Consumption

Although there is considerable literature on the effects of energy-related emissions and climate mitigation policies, research on how climate change impacts the energy sector is relatively scant (Mideksa and Kallbekken, 2010). The literature on how climatic variables influence energy consumption shows statistically significant effects of climate change on energy demand, with the results being consistent across different locations and time periods. Empirical studies point out that climate changes, such as an increase in the number of hot or cool days, could affect household energy consumption. Deschênes and Greenstone (2011) examine residential energy consumption in nine different temperature bins from 1968 to 2002 in the US and find a clear U-shape relationship between energy demand and temperature. The existing literature on the impacts of climate change on the energy sector lacks regional coverage in Asia, Africa, and South America and neglects the relationship between extreme weather and electricity demand (Mideksa and Kallbekken, 2010). Our study contributes to the literature by examining how extreme air pollution shocks in Southeast Asia affect water and energy consumption in the residential sector.

The detrimental effects of air pollution on health and productivity have garnered attention from economists in recent years. Studies have shown alarming evidence of the negative impacts of air pollution on infant health. Chay and Greenstone (2003a) show that approximately 1,300 fewer infants died in 1972 than would have without the Clean Air Act Amendments of 1970. They also show 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 0.35% decline of the infant mortality rate is reported in a separate study by Chay and Greenstone (2003b) for the period between 1980 and 1982. In addition to the reduction of PMs, reductions of other pollutants, such as carbon monoxide (Currie and Neidell, 2005) and nitrogen oxide (Deschênes et al., 2017), could also reduce the mortality rate[6].

In addition to the health-related consequences, 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 (Graff Zivin and Neidell, 2012; Bento et al., 2015; Chang et al., 2016; Heyes et al., 2016; Deschênes et al., 2017; Agarwal et al., 2018).

Although air pollution and its detrimental effects on health and the ecosystem have been studied in great depth, little is known about the human consumption of basic needs, such as water and electricity, in response to changing air quality. Our study contributes to the current knowledge by analyzing the impact of air pollution on the consumption of water and electricity, two critical resources during extreme weather conditions.

Moreover, few studies have measured the defensive investments or mitigation behaviors associated with climate change (Deschênes et al., 2017). Some empirical studies have found evidence on the risk avoidance behaviors of individuals who take various preemptive steps to minimize their exposure to environmental risks by staying indoors (Zivin and Neidell, 2009; Neidell, 2009). In response to environmental risk alerts, individuals may increase their use of household appliances, such as air purifiers (Chay and Greenstone, 2003b; Currie and Neidell, 2005; Ito and Zhang, 2016) and air conditioners (Agarwal et al., 2016), or change their consumption behaviors, such as consuming less canned fish (Shimshack et al., 2007), drinking bottled water (Zivin et al., 2011), and using more electricity (Yang, 2017).

The empirical evidence of human behavioral responses to 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 clean identification of the endogenous relationship between air pollution and human activities. Our study finds a random 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, 2003a; Bento et al., 2015), others use temporal variations in the levels of different pollutants, such as total suspended particulates (Chay and Greenstone, 2003b), ozone (Currie and Neidell, 2005; Graff Zivin and Neidell, 2012; Chang et al., 2016),

---

[6] Currie and Neidell (2005) estimate that the reduction in CO that occurred during the 1990s saved approximately 1,000 infant lives in California. Deschênes et al. (2017) 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 nitrogen oxide (Deschênes et al., 2017), and the year-to-year changes in temperature (Deschênes and Greenstone, 2011; Deschenes, 2014) to set up exogenous shocks to test for the environmental effects on human health outcomes and activities. A recent study (Jia and Ku, 2015) examining the transboundary air pollution from China to South Korea exploits exogenous incidences of dust and finds that an increase in the pollution levels in China leads to an increase in the number of deaths associated with respiratory and cardiovascular illnesses in South Korea. The unique setting of our study allows for a clean identification of the causal effects of air pollution on energy consumption.

While our analysis provides empirical evidence of air pollution in a developing country, our results can be generalized to developed countries, such as the US and Canada, which face similar air pollution issues. The general public and governments of Asian countries, particularly those in China, Korea, Singapore, and Indonesia, have been concerned about particulate air pollution. Rosales-Rueda and Triyana (2018) 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. Recent research focuses on measuring the behavioral responses to air pollution in China. Using television viewership to infer the impacts of pollution on the amount of time spent indoors and the economic costs, Viard and Fu (2015) find that the driving restrictions in Beijing are associated with a 21% decrease in particulate matter. Zhang and Mu (2017) provide empirical evidence on the avoidance behaviors of urban residents in China who purchase particulate-filtering masks. They find that a 10% reduction in the number of extreme pollution days in China would result in a total savings on masks of approximately US$187 million. Similarly, Ito and Zhang (2016) investigate the use of household air purifiers to determine the preference estimates of the willingness to pay for clean air.

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

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

In the ASEAN region, nearly all of the fires and haze over the past two decades have been caused directly by human intervention rather than by natural events (Qadri, 2001). 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[7]. While the burning-related air pollution is mostly caused by local sources of emissions, 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.

Since haze pollutant contains carbon dioxide and sulfur dioxide, along with aerosols and toxic particulates as well as a strong acrid and burning smell, it is easily detectable by public, and the air is clearly distinguishable from that of normal days without haze. 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. The transboundary haze events in Indonesia, which are likely to generate unanticipated and immediate effects on human activities, are used as exogenous shocks in our study[8]. In particular, the fluctuations of air pollutants in Singapore are merely dependent on local economic activities and seasonal changes, but are highly correlated with the forest fires in neighboring Indonesia.

In recent years, recurring peatland and forest fires have been the main causes of haze problems in Southeast Asia, 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 (Singapore PSI is reported as a number on a

---

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

[8] 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. (2015) studied the consumption responses of affected employees and found that most households have mechanisms to smooth consumption to cope with income and liquidity shocks.

scale of 0 to 500). Two senior diplomats made the following comments in a local newspaper: *"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.*[9]"

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. Based on the sources cited by the Wall Street Journal, the Indonesian government alone incurred an estimated US$14 billion in haze-related economic losses, environmental damage, health expenses, and business losses[10]. 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[11], makes haze pollution information freely available to the public. The NEA reports and disseminates one-, three-, and 24-hour PSI[12] readings on a regular basis to inform residents of air quality via mass media, such as television, radio, the Internet, and mobile applications. For ease of reference, the NEA also provides five different PSI descriptors (as shown in Table 1) to indicate the levels of pollution risks based on the PSI measures and the Ministry of Health (MOH) offers general advisories for various stakeholder groups accordingly[13].

[**Table 1 inserted here**]

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

---

[9] 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.

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

[11] 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.

[12] Compared to Air Quality Index(AQI), PSI is determined by the pollutant with the most significant concentration.

[13] Source:http://www.haze.gov.sg.andhttp://www.nea.gov.sg/corporate-functions/newsroom/news-releases/singapore-government-agencies-coordinate-effort-to-mitigate-haze-impact-on-public

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. A school continuity plan is set in place by the Ministry of Education (MOE) to ensure the safety of staff and students during a haze situation, with normal school activities resuming only if the 1-hour PSI value is under 100. 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.

4 Data Sources

We collect data from multiple sources and the data can be grouped into two broad categories: utilities consumption and measures of ambient conditions. Table 2 reports summary statistics for our datasets on hourly and monthly basis.

[**Table 2 inserted here**]

4.1 Utilities Consumption

4.1.1 Household Water-Consumption Data

We obtain a unique dataset containing the hourly water-consumption records of a random sample of 376 households from nine public housing flats[14] 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.

For each sample household, we have information about their hourly water consumption, ethnicity, dwelling type, 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[15]. 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

---

[14] 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.

[15] 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.

the day, within the week, and within the month (with different weather conditions) in our analyses.

We conduct an empirical analysis on an hourly basis for water consumption data, and on a monthly basis for electricity consumption data. 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, and then aggregate the daily average PSI readings into the monthly averages to perform an analysis of the monthly electricity consumption data. During the study period, the extreme haze episodes lasted 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.

4.1.2 Building Electricity Consumption Data

We collected the average monthly electricity consumption data in kWh of four different dwelling types (one/two-, three-, four-, and five-room/executive) at the building level (where each building is identified by a unique postal code in Singapore) for 9,016 public and 4,079 private residential buildings in Singapore for the period between January 2013 and December 2016. The data are provided by the EMA in Singapore.

Since Singapore is a small island spanning 709 square kilometers, air pollution is homogeneously spread island-wide, which means everyone in Singapore is exposed to the air pollutants. There are five monitoring stations in Singapore, which cover five regions based on the town centers. Using the guide provided by the National Environment Agency[16], the pollution level of buildings is assigned to the corresponding monitor station. To increase the precision of pollution measurement, we use ArcGIS to find the nearest station to each building, and use the PSI reading of the nearest to proxy the air pollution exposure of the building for town centers not listed on the guide. 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).

[Figure 1 inserted here]

4.2 Pollution and Weather Measures

4.2.1 24-Hour PSI Readings and Satellite Fire Data

The exogenous haze shocks generated by forest fires in Indonesia are captured by the 24-hour Pollutant Standard Index (PSI) in Singapore. The National Environment Agency (NEA) in Singapore provides the hourly PSI readings between January 1, 2012 and December 31, 2016.

---

[16] See details on $https://www.nea.gov.sg/our-services/pollution-control/air-pollution/faqs$

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 (in red) from January 1, 2012 to December 31, 2016 in Figure 2.

[**Figure 2 inserted here**]

The PSI is a composite measure of the concentrations of multiple pollutants, which includes particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$)[17], sulfur dioxide (SO_2), nitrogen dioxide (NO_2), Ozone (O_3), and carbon monoxide (CO). The PSI readings provide a more accurate and comprehensive measure of air pollution than a single pollutant reading does. However,the 24-hour PM2.5 concentration (in g/m^3) were recorded separately from Aug 24, 2012 to Mar 31, 2014, and subsumed into PSI from Apr 1, 2014. Therefore, the upward trend of the PSI reading may be accounted for by the incorporation of the PM2.5.

To address the concern that we may have used an inconsistent measure of PSI reading, we construct an adjusted measure of PSI that incorporates PM2.5 before April 1, 2014 using the same method that NEA used for constructing PSI reading. The computation of the PSI is provided in Appendix B. Figure 2 presents the adjusted PSI readings in green. As a robustness check, we included an indicator variable $PSIchange_t$, which is a binary variable for the inclusion of PM2.5 into the PSI reading after Apr 1, 2014, in our specification, for the incorporation of $PM_{2.5}$ in the PSI reading after April 1, 2014.

Moreover, to strengthen the causal relationship between utilities consumption in Singapore and the transboundary haze pollution originated from Indonesia, we collect the fire radiative power (FRP) in megawatts (MW) from all Indonesian latitudes and longitudes between January 1, 2012 to Dec 31, 2015. The data was obtained from the Fire Information for Resource Management System at National Aeronautics and Space Administration (NASA). We further aggregate the FRP data into hourly and monthly as the fire variables for water and electricity analysis. The average hourly FRP during the sample period is 6.62MW, ranges from 0 to 995.27MW. Figure 3 plots the daily average FRP (top graph) and the daily aggregated FRP (bottom graph) measured in megawatts (MW) in Indonesia during the period.

[**Figure 3 inserted here**]

4.2.2 Weather Information

Poor weather conditions could be possible confounders of the influence of air pollution in households' decisions to stay indoors and consume water and electricity. To resolve this

---

[17] $PM_{2.5}$ 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).

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 2016. The data contain hourly information on temperature, humidity, air pressure, and wind speed. The hourly weather measures are used for hourly water consumption analysis and hourly demand for electricity analysis.

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 for the monthly electricity consumption analysis. 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.

4.2.3 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."*

[**Figure 4 inserted here**]

We measure the total number of tweets that contain the above keywords per hour and their responses. Using the sentiment analysis technique[18], we analyze the contents of the tweets and assign each tweet an emotion score ranging from -1 to 1 (a continuous number). 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.

---

[18] 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 ?? shows the hourly tweets generated by Singapore users during the major haze episodes. Figure 4 shows the proportion of tweets with negative emotions posted every month, which account for as much as one-quarter of all haze-related tweets during the peak haze hours.

5 Empirical Methodology and Strategy

5.1 Empirical Models

5.1.1 A Pollution-Shock Approach

Following Jayachandran (2009); Dell et al. (2014), we first use a pollution-shock approach, which regresses the outcomes of utilities consumption on a measure of air pollution, to examine the impact of air pollution on energy consumption. Exogenous climate and weather shocks may substantially influence economic performance. This weather-shock method has compelling identification characteristics and it permits remarkably strong causative interpretation. Several studies have examined extreme windstorms (Yang, 2008; Nordhaus, 2010; Hsiang and Narita, 2012) and have shown higher wind speeds present in substantially larger economic losses. As the haze episodes occurred in Singapore is random and exogenous, the reduced-form panel pollution-shock approach makes few identification assumptions and allows strong causative interpretation (Dell et al., 2014).

The continuous hourly 24-hour PSI reading is an hourly measure over a rolling 24-hour period and is the most direct way of measuring the haze intensity[19]. In addition, 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. Our basic reduced-form regression model is as follows:

$$Consumption_{i,t} = \beta PSI_{r,t} + \cdot Weather'_{l,t}\gamma + \tau_t + \lambda_i + \epsilon_{i,t} \tag{1}$$

where the dependent variable, $Consumption_{i,t}$, is the periodic logarithmic term of the hourly household water consumption, the monthly building electricity consumption for each household or building i at the end of t, or the hourly electricity demand at the end of t. $PSI_{r,t}$ is the logarithmic term of the adjusted 24-hour PSI reading at each weather station r[20]. β

---

[19] The hourly 24-hour PSI reading is less volatile than the spot hourly PSI reading (one-hour PSI reading, which was reported only after 2017), therefore, our sample of hourly haze measurements does not contain observations greater than 300, which is considered “hazardous” to human health. Moreover, the hourly 24-hour PSI readings 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.

[20] There are five air-quality monitoring regions in Singapore, as shown in Figure 1.

captures the average periodic energy consumption during the haze episodes. This first step allows us to predict how changes in utilities consumption are associated with the percentage increases in the 24-hour PSI reading.

The weather conditions could influence the haze effects, for instance, households are more likely to use more water (e.g., take more baths) during warmer days. Thus, we try to separate the possible confounding effects of weather conditions on household water-consumption decisions from the haze pollution. To produce more precise estimates, we add a vector of other time-varying observations, $Weather'_{l,t}$, which include the logarithmic terms of temperature, humidity/rainfall, air pressure and wind speed at each weather station l at time t.

τ_t is the year, month, and hour 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, further neutralize any common trends to ensure that the relationships of interest are identified from idiosyncratic local shocks. Finally, λ_i is the household fixed effect in water consumption, which is included to absorb the systematic differences in the water usage preferences at the household level. In the electricity consumption analysis, λ_i is the building level fixed effect, which absorb fixed spatial observable or unobservable characteristics, disentangling the shock from many possible sources of omitted variable bias. 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

We study the dynamic relationship between the changes in air quality and the behavioral changes of households following (Agarwal and Qian, 2014). In particular, we examine how much effect the haze episode has on utilities consumption, when it has the effect, whether the effect is immediate, and whether the effect goes away a few periods. More importantly, we study whether the haze effects on utilities consumption varied based on the duration of air pollution events.

We use an "event study" approach to identify a short-term haze episode and a long-term haze episode during the period. Figure 2 plots the 24-hour PSI readings from January 1, 2012 to December 31, 2016. The red line represents the variation of 24-hour PSI readings and the green line stands for adjusted 24-hour PSI measure. PM2.5 before April 1, 2014 are plotted in blue. The shaded areas stand for two severe haze shocks in June 2013 and September 2015. The width of the shaded areas represents the duration of air pollution events. The short-term air pollution shock occurring in mid-June 2013 is shown in the corresponding spike of the two charts. The long-term air pollution episodes occurred in Singapore between September 2015 and October 2015.

We denote the haze period as the event period (t=0) and consider the pre-haze and post-haze periods and estimate the following distributed lag model:

$$Consumption_{i,t} = \sum_{s=-6}^{6} \beta_s PSI_r \cdot 1_s + \cdot Weather'_{l,t}\gamma + \tau_t + \lambda_i + \epsilon_{i,t} \tag{2}$$

Here, the coefficient β_s measures the immediate water usage response during a haze period (the third week of of Jun 2013). $[\beta_1, \ldots, \beta_6]$ are the marginal coefficients that measure the additional water consumption responses from the current period up to six periods after the haze event compared to the benchmark period, i.e., the first two weeks of May (Apr 29 to May 12) in 2013. Similarly, the coefficients $[\beta_{-1}, \ldots, \beta_{-6}]$ capture the changes in the consumption trends from six periods before the haze event. 1_s is a binary variable that is equal to 1 in period s[21].

To examine the cumulative impact of haze episodes on utilities consumption, we use the cumulative coefficient $b_s = \sum_{t=-6}^{6} \beta_t$ to describe the cumulative response of water or electricity usage after s periods. For instance, when the water consumption increases by $beta_0$=0.19 during the haze shock and rises by $beta_1$=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 and electricity consumption before the haze episodes, and we expect the coefficient to be economically and statistically insignificant.

5.1.2 An Instrumental Variable Approach

Since the PSI reading in Singapore is monitored through a network of air monitoring stations located in different parts of the island and PSI is computed on the concentration of PM2.5, the dominant pollutant during haze episodes, along with other five pollutants, such as SO2, PM10, NO2, CO, and O3, it is possible that the PSI readings capture pollution from local activities. .

To provide evidence that the increases in 24-hour PSI readings in Singapore are caused by the forest fires in Indonesia rather than pollution at the local level, we provide an improved estimation of haze effects on utitilies consumption using satellite fire data to instrument for the tranboundary haze episodes. We estimate the following two-stage least equations by instrumenting for haze pollution in Singapore with forest fire in Indonesia:

$$PSI_{r,t} = \theta_1 FRP_t + Weather'_{l,t}\beta_1 + \tau_t + \lambda_i + \epsilon_{i,t} \tag{3}$$

---

[21] In the electricity consumption analysis, September and October 2015 is the haze period, and Apr to May 2015 is the benchmark period. The coefficient β_s measures the immediate electricity usage response three months before and after the haze period

$$Consumption_{i,t} = \theta_2 \widehat{PSI_{r,t}} + \cdot Weather'_{l,t}\beta_2 + \tau_t + \lambda_i + \epsilon_{i,t} \tag{4}$$

where $PSI_{r,t}$ is the adjusted hourly or monthly 24-hour PSI reading for the air pollution region r at time t. FRP_t is the fire radiative power in Indonesia. $\widehat{PSI_{r,t}}$ is the predicted value of the PSI from the estimation of Equation (3). τ_t is time fixed effects and λ_i is the household/building fixed effects. Standard errors are clustered at the household level for the water consumption analysis, and at the building level for the electricity consumption analysis.

5.2 Testable Hypotheses on Risk avoidance and Mitigation Behavior

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. Many 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. While some household uses of water and electricity, such as cooking, are not strongly linked to climate change, other household uses, such as cleaning and air conditioning, directly contribute to the climate crisis.

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 behavior 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. An increase in water consumption also reflect an increase in mitigation behaviors. As suggested by MOH, households drink more water to flush out toxins, take longer showers, and clean more thoroughly after their exposure to air pollutants.

Our study is designed to identify the causal relationship between air pollution and utilities consumption and to empirically examine the underlying mechanisms driving the changes on utilities consumption. Utilizing the hourly household consumption and pollution data, we explain the mechanism by which the haze effects impact water and electricity consumption. To better understand household utilities 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 during daytime on weekdays. Mitigating the health risks of air pollution happens in the period after the exposure to air pollution events and the utilities consumption behavior may change at night due to the daytime exposures to pollutants. Thus, 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: Utilities usage remains unchanged during daytime on weekdays.

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 daytime weekdays.

Hypothesis 2: Utilities usage increases significantly at night.

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.

Hypothesis 3: Changes on utilities usage vary based on the severity of haze measures during weekends.

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 utilities 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 "unhealthy" 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. 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, we examine the three testable hypotheses to understand the underlying mechanisms by which different levels of air pollution affect consumption behavior. We expect the coefficients that measure the impacts of haze on utilities consumption to be significantly positive at night on weekdays, insignificantly during the day on weekdays, and significantly positive at night on weekends. The sign of the coefficient of the effects depends on the severity of haze episodes during the day on weekends.

6 Main Results

6.1 Haze Effects on Water and Electricity Consumption

First, we examine the causal effects of the haze pollution that occurred from 2012 to 2016 using data on the hourly water consumption of households and the monthly electricity consumption of residential buildings. Tables 3 and 4 presents the haze effects of water consumption and electricity consumption, respectively. We use two approaches to deal with the inclusion of PM2.5 in the PSI reading after April 1, 2014 (see more explanations in Section 4.2.1.). Panel A presented the results using the adjusted PSI as the pollution measure and Panel B shows the robustness check that uses an indicator variable $PSIchange_t$ and the PSI reading for the incorporation of PM2.5 into the PSI before April 1, 2014. We begin by estimating an ordinary least square (OLS) model and then a 2SLS model. Columns 1 and 4 show the OLS estimates, Columns 2 and 5 show the first stage results of IV, and Columns 3 and 6 present the IV estimates.

The results show a highly significant positive response in the hourly water consumption in relation to the change in the haze measures. The coefficient in Column 1 of Table 3 estimates that a 100% increase in the 24-hour PSI reading causes hourly water consumption to increase by 6.9%. The estimation of Equation (3) shows that Indonesia's FRP is a statistically significant determinant of PSI reading in Singapore. The estimation of Equation (4) indicates that a 100% increase in the predicted PSI reading in Singapore causes the hourly water consumption to increase by 14.3%. The results in Panel B are consistent with that in Panel A.

[Table 3 inserted here]

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 Equations (1), (3), and (4). The haze effects, as represented by $ln(adjustedPSI)$, are statistically and economically significant in all models. The OSL estimate shows that a 100% increase in the monthly average 24-hour PSI value increases the building-level electricity consumption by 3.7%. The IV estimate suggests that a 100% increase in PSI readings yields a 7.9% increase in monthly electricity consumption. The results in Panel B are statistically significant and are consistent with that in Panel A.

[**Table 4 inserted here**]

6.2 Risk avoidance and Risk mitigation Behavior: Evidence from Hourly Water Consumption

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 intra-day (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[22]. We find evidence of the risk avoidance and risk mitigation behaviors by examining the within-the-day hourly water-consumption behaviors of households during the haze periods.

Table 5 reports the estimation results separated by weekdays and weekends using the hourly water consumption and haze data from January 1, 2012 to December 31, 2014. Columns 1 and 4 in Panel A show that the effect of PSI readings 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 2) and weekends (Column 5). The coefficient of ln(24-hour PSI) is significant only when predicting weekends 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-

---

[22] 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.

hour PSI value) in Columns 3 and 6 of Table 5 indicates that a 100% increase in the 24-hour PSI value is associated with 6.44% and 9.84% 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, which suggests the households try to mitigate the risk of exposure to air pollutants during daytime.

In addition, we examine the impact of $PM_{2.5}$ on water consumption in Panel B of Table 5. $PM_{2.5}$ causes severe health related consequence as the fine particulate matter can be inhaled deep into the lungs and enter to the bloodstream. The results are presented in Panel B and consistent with the previous findings. Based on the positive relationship between the $PM_{2.5}$ level and water consumption during nighttime and insignificant or negative effects during daytime, we could not reject the risk avoidance hypothesis and risk mitigation hypothesis.

[**Table 5 inserted here**]

Table 6 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, $HeavyHaze$, in the model specification to represent different thresholds of the hourly 24-hour PSI values, ranging from 80 to 200. In Column 1, $HeavyHaze$ 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, $HeavyHaze$*$Night$, which measures the difference between the daytime and nighttime haze effects.

To understand whether households' utilities consumption response is a results of people perceiving bad air quality or a response to the haze warning issued by government, we employ a regression discontinuity (RD) to analyze the impact of air quality warning on consumption behavior. Following **?**, we use the decision rule for issuing warnings (PSI≥100 and PSI≥200) to compare utilities consumption on periods just at the warning threshold with periods just below the threshold. The major assumption of the RD design is that periods with PSI readings just below the threshold were comparable to periods just at the threshold, other than the warning itself. We test whether periods around the threshold were comparable by assessing whether observable characteristics balance.

Appendix Figure A1 plots the conditional mean of the water consumption across the haze warning thresholds (PSI=100 in the left panel and PSI=200 in the right panel). Linear fitted lines are based on regressions of water consumption on baseline covariates from Jan 1, 2012 to Dec 31, 2014 on a linear polynomial in PSI reading. We plot 5 to 20 readings around the 100, and 20 to 40 readings around 200 due to limited observations around the cutoffs. The results indicate that utilities consumption is not associated with significant increases when haze alerts were issued. Therefore, the response in utilities consumption is a result of people perceiving bad air quality.

[Table 6 inserted here]

The weekday water-consumption models are shown in Panel A of Table 6. The coefficients of the Night dummy variable show that water consumption after 6 pm is higher than that of the daytime on typical weekdays. 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. Most importantly, we find that nighttime water consumption increases by an average of 6.68% to 9.36% during the haze periods, as indicated by the interaction term, $HeavyHaze*Night$. These results are consistent with the household risk mitigation behavior, which are evident during the weekdays. Individuals cannot easily avoid haze due to work or school commitments during the daytime on weekdays, and they return home and consume more water for cleaning and washing purposes; thus, they use more water at night on weekdays during the haze periods.

We use the same regression models to analyze the household water consumption during the weekends, and the results are presented in Panel B of Table 6. We find more discerning evidence of risk avoidance when we study the interactions of the $HeavyHaze$ and $Night$ variables in the models. The results in Column 1 of Panel B 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. With mild-haze shocks, the haze effect on nighttime water consumption is larger than that on the daytime consumption because households may still choose to go out during the day on weekends. However, when the 24-hour PSI values reach 100 or more, the $HeavyHaze*Night$ coefficients are positive but insignificant, suggesting that the different haze effects are marginally indifferent for the daytime and nighttime water consumptions on weekends. The insignificant coefficients on Column 2 to 4 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 and they are more likely to refrain from going out on weekends at the expense of being exposed to haze risks.

Since the increase in household electricity and water consumption may be partially offset by the reduced use of water and electricity outside of residential building due to individuals' risk avoidance and mitigation behavior, it is important to study the aggregate effect of pollution on energy consumption. We conduct a supplementary analysis to assess the impact of transboundary air pollution on electricity demand in Singapore. In particular, we utilize data on hourly electricity system demand (MW) from the Energy Market Authority, which captures the electricity demand in both the residential and commercial sectors. We estimate the causal relationship between PSI readings and electricity demand following a standard OSL regression in Equation (1) and two-stage least square equations in Equations (3) and (4).

The results are presented in Appendix Table A1, and we find that the aggregate effect on residential and commercial establishments are positive. More specifically, the estimation of Equation (1) indicates that a 100% increase in the 24-hour PSI reading is associated with 2.5% increase in electricity demand. The estimation of Equation (3) shows that Indonesia's FRP is a statistically significant determinant of the 24-hour PSI reading in Singapore at the 1% level. The results from estimating Equation (4) show that a 100% increase in the predicted 24-hour PSI in Singapore causes a 11.4% increase in the demand for electricity in all buildings in Singapore (including both commercial and residential sectors). All the estimated coefficients are statistically significant at the 1% level. Taken together, these results in Appendix Table A1 and Table 4 show that the transboundary haze pollution leads to positive energy usage in both residential and commercial buildings.

6.3 Dynamics of Consumption Responses to Short-term and Long-term Pollution Events

Next, we look at the dynamics of the consumption responses as a function of the pollution shock. Panel A of Figure 5 shows the weekly water-consumption trend 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 the third week of June 2013. 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 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_s, and the dashed lines represent the corresponding 95% confidence intervals. The results suggest that people may revert to their usual daily norms after the temporary haze has dissipated.

[**Figure 5 inserted here**]

Moreover, we analyze the dynamic monthly electricity consumption trends when the haze shrouded Singapore during the first week of September and the third week of October in 2015. We plot the dynamic monthly (Panel A) and cumulative month-to-month electricity consumptions (Panel B) in Figure 6 and do the same for a seven-month window analysis. The two-month long haze shocks are coded using the year-month variable with the corresponding numbers of "668" (September 2015) and "669" (October 2015).

[Figure 6 inserted here]

We find that significant higher 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 remain at a higher level in the two months following the long-term shocks.

6.4 Air Pollution and Social Awareness: Evidence from Twitter Data

The role of emotions has been largely ignored in determining household energy consumption. Raghunathan and Pham (1999) posit that negative emotions may shape decision-makers' motives and, thus, determine decisions. Qin and Zhu (2018) investigate the impact of air pollution on people's interest in emigration, and report that on the day after a 100-point increase in air quality index, online searches of the topic "emigration" increase by about 4.8%. Our collection of Twitter data as a proxy of the changes in awareness during the study period provides a unique identification strategy in the study the impact of awareness and 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[23]. Moreover, our Twitter-data analysis is based on the daily aggregation of hourly Twitter data. Figure 5 plots the total tweet count (blue line) and the number of tweets with negative emotion score per month (red line). Table 7 presents the relationship between the number of haze event 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 2.2% when the number of haze-related tweets doubles. Further, we sort the tweets by topic into three

---

[23] 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.

broad categories—*"Haze," "Environment,"* and *"Health"* (see Figure 5)—and estimate the water-consumption response models in Columns 2 to 4. We estimate the water-consumption responses to the Twitter scores as having magnitudes varying from 0.1% for the *"Haze"* category to 1.6% for the *"Environment"* category. When we use only the tweets with negative emotions, the *"Health"* category (Column 4) generates stronger water-consumption responses of 3.09%, which suggests that households who tweet more on the issues related to the health consequences or concerns show stronger responses in their water consumptions.

[Table 7 inserted here]

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. To assess whether public awareness of air pollution events contribute to the changes on household water consumption, we use the number of daily twitter counts as a proxy of social awareness and emotion change toward haze episodes. We conduct regression analysis on a daily basis by aggregating hourly water consumption into daily consumption and present the results in Table 8 . Columns 1 to 3 use the logarithm of daily maximum PSI reading as independent variable and Columns 4 to 6 use the logarithm of daily average PSI reading as independent variable, and all coefficients are statistical significant and positive. Columns 1 and 4 explore the linear relationship between PSI and water consumption. Columns 2 and 5 include additional weather controls, such as temperature, humidity, air pressure, and wind speed. In Columns 3 and 6, we further include the logarithm of total number of related tweets. The inclusion of the twitter counts decreases the magnitudes of the coefficients on the pollution measure and the public consciousness of haze conditions explains 17.7% to 23.6% of the haze effects, suggesting the potential mechanism of haze pollution affect utilities consumption.

[Table 8 inserted here]

In addition, like Raghunathan and 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 Appendices).

6.5 Robustness, Falsification and Heterogeneity Tests

We use the propensity score matching (PSM) method to deal with the alternative explanation that weather conditions, such as temperature, humidity, pressure, wind speed, and rain status, could be possible confounding factors that affect the household utilities consumption behavior. More specifically, 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

PSM. For matching purposes, we create a *hazedummy* to represent the treatment period, where the *hazedummy* is equal to 1 when the hourly PSI readings at said period exceed the referenced cutoff and is 0 otherwise (the control period).

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 consumption 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 A3). The PSM significantly reduces the post-matching differences between the treatment and control periods in all observable weather conditions.

We use four different cutoffs [24-hour PSI=60, 70, 100, and 150] to identify the treatment periods in our experiment and use four different subsets of matched samples following Equation (1) and present the results in Table 9. Columns 1 to 4 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 1) and 70 (Column 2), 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 statistically insignificant when the more stringent PSI cutoff of 100 and 150 are used. The results imply that water-consumption behavior is positively influenced by increases of the haze-shock intensities. Households are more sensitive to the haze shocks when the PSI readings go above 100, which is in the "unhealthy" range.

[Table 9 inserted here]

Next, to address the concern that the significance on estimated coefficients may arise randomly, we perform falsification tests 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.

[Figure 7 inserted here]

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 A4 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.

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[24] have established that the concentration of air pollutants (e.g., PM10, PM5, PM2.5, and PM1) decreases with respect to building height, but the studies find different vertical distributions of the pollutants above ground level[25]. Panel C of Table A3 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 20th floor. However, the responses of households living on the higher floors (between the 21st and 25th 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 21st floor.

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

---

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

[25] Researchers at Tsinghua University, who studied the haze concentrations in Beijing from October to December 2003, show that large variations in the concentrations of PM2.5 in the air are found in the range of eight to 32 meters above the ground (approximately between the second and 10th floors of a building), and the PM2.5 concentration decreases by 19% at a height of 64 meters from the ground (approximately at the 20th 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.

consumption more than smaller flat types (usually occupied by single or married but without children residents).

Based on both the private-housing and resale-public-housing transaction price data, available from public sources[26], 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 A5). 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.

7 Quantifying the Additional Costs Associated with Haze Pollution

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 the 2sls estimation suggest that, as the haze readings double, the average household-level hourly water consumption increases by 14.3% and the average building-level monthly electricity consumption increases by 7.9%. 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 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 utilities 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 71.5% and 39.5%, respectively, on a linear scale.

Using the informal estimation method, we convert the increases in water and electricity consumption into the economic costs[27] of the negative externalities caused by the forest

---

[26] 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.

[27] 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

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.

As shown in Table A5 of Appendices, 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\$14.82 million, US\$10.41 million) and Scenario (2) (S\$74.11 million,US\$52.06 million) when the PSI readings increase by 100% and 500%, respectively[28].

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\$4.03 million (US\$2.83 million) for Scenario (1) and S\$20.13 million (US\$14.14 million) for Scenario (2) when the PSI readings increase by 100% and 500%, respectively.

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 in the residential sector alone, are estimated to be around S\$94.24 million (US\$66.21 million), (\$70.2 per household) annually.

Although the externality costs on water and electricity consumption incurred in Singapore could be a marginal fraction of total externalities costs, including explicit environmental costs, health expenses, and business losses, 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.

Consumers consume more water and electricity due to risk avoidance and risk mitigation behaviors during the haze episode. However, the unnecessary use of energy resources after air pollution events due to habit formation during haze episodes would lead to the rapid depletion of conventional type of resources. Studies show that energy conservation programs initiated by government has only achieved little success compared to the haze effects on energy consumption. Agarwal et al. (2017) show that energy consumption campaign in

---

m^3 and 45% for consumption above that.

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

Singapore creates persistent electricity savings of 1.6% in the post campaign months. Our study shows that a mild haze shock increases electricity consumption by 4.16%, suggesting a new challenge that policy makers and advocates for energy conservation should pay attention to and deal with.

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 utilities consumptions increase significantly during haze periods.

This paper uses multiple sources of outcome data describing household water consumption and building electricity consumption, and then 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 utilities consumption. The results from estimating the 2SLS regressions show that FRP in Indonesia is a strong instrument for PSI in Singapore, and a 100% increase in the predicted 24-hour PSI value is associated with a 14.3% increase in water consumption and a 7.9% increase in electricity consumption. We provide three new contributions to the current literature.

Second, we find robust empirical evidence of the risk avoidance and risk mitigation 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.

Moreover, 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. In particular, the public consciousness of haze conditions, as represented by the daily twitter counts, explains 17.7% to 23.6% of the haze effects, suggesting the potential mechanism of haze pollution affect utilities consumption.

Third, we find that the haze effects of household utilities 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 behavioral responses of households to the haze risks.

This study measures the causal impact of air pollution on utilities consumption and 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 utilities 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 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, local communities, and utilities suppliers for demand forecasting when similar events occur in the future. The findings of the partial economic-welfare effects associated with increased utilities consumption 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.

References

Abatzoglou, J. T. and A. P. Williams (2016). Impact of anthropogenic climate change on wildfire across western us forests. *Proceedings of the National Academy of Sciences 113*(42), 11770–11775.

Agarwal, S. and W. Qian (2014). Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in singapore. *American Economic Review 104*(12), 4205–30.

Agarwal, S., S. Rengarajan, T. F. Sing, and Y. Yang (2017). Nudges from school children and electricity conservation: Evidence from the "project carbon zero" campaign in singapore. *Energy Economics 61*, 29–41.

Agarwal, S., R. Satyanarain, T. F. Sing, and D. Vollmer (2016). Effects of construction activities on residential electricity consumption: Evidence from singapore's public housing estates. *Energy Economics 55*, 101–111.

Agarwal, S., L. Wang, and Y. Yang (2018). Blessing in disguise? environmental shocks and performance enhancement. *Working Paper*.

Bayer, P., N. Keohane, and C. Timmins (2009). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management 58*(1), 1–14.

Bento, A., M. Freedman, and C. Lang (2015). Who benefits from environmental regulation? evidence from the clean air act amendments. *Review of Economics and Statistics 97*(3), 610–622.

Brandt, L. and T. G. Rawski (2008). *China's great economic transformation*. Cambridge University Press.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy 8*(3), 141–69.

Chay, K. Y. and M. Greenstone (2003a). Air quality, infant mortality, and the clean air act of 1970. Technical report, National Bureau of Economic Research.

Chay, K. Y. and M. Greenstone (2003b). The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. *The Quarterly Journal of Economics 118*(3), 1121–1167.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? evidence from the housing market. *Journal of Political Economy 113*(2), 376–424.

Currie, J. and M. Neidell (2005). Air pollution and infant health: what can we learn from california's recent experience? *The Quarterly Journal of Economics 120*(3), 1003–1030.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature 52*(3), 740–98.

Dennison, P. E., S. C. Brewer, J. D. Arnold, and M. A. Moritz (2014). Large wildfire trends in the western united states, 1984–2011. *Geophysical Research Letters 41*(8), 2928–2933.

Deschenes, O. (2014). Temperature, human health, and adaptation: A review of the empirical literature. *Energy Economics 46*, 606–619.

Deschênes, O. and M. Greenstone (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics 3*(4), 152–85.

Deschênes, O., M. Greenstone, and J. S. Shapiro (2017). Defensive investments and the demand for air quality: Evidence from the nox budget program. *American Economic Review 107*(10), 2958–89.

Dominici, F., M. Greenstone, and C. R. Sunstein (2014). Particulate matter matters. *Science 344*(6181), 257–259.

Gelman, M., S. Kariv, M. D. Shapiro, D. Silverman, and S. Tadelis (2015). How individuals smooth spending: Evidence from the 2013 government shutdown using account data. Technical report, National Bureau of Economic Research.

Graff Zivin, J. and M. Neidell (2012). The impact of pollution on worker productivity. *American Economic Review 102*(7), 3652–73.

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. *Journal of Political Economy 110*(6), 1175–1219.

Heyes, A., M. Neidell, and S. Saberian (2016). The effect of air pollution on investor behavior: Evidence from the s&p 500. Technical report, National Bureau of Economic Research.

Hsiang, S. M. and D. Narita (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics 3*(02), 1250011.

Ito, K. and S. Zhang (2016). Willingness to pay for clean air: Evidence from air purifier markets in china. Technical report, National Bureau of Economic Research.

Jayachandran, S. (2009). Air quality and early-life mortality evidence from indonesia's wildfires. *Journal of Human resources 44*(4), 916–954.

Jia, R. and H. Ku (2015). Is china's pollution the culprit for the choking of south korea? evidence from the asian dust. Technical report, Working Paper.

Kasischke, E. S. and M. R. Turetsky (2006). Recent changes in the fire regime across the north american boreal region—spatial and temporal patterns of burning across canada and alaska. *Geophysical research letters 33*(9).

Mansur, E. T., R. Mendelsohn, and W. Morrison (2008). Climate change adaptation: A study of fuel choice and consumption in the us energy sector. *Journal of Environmental Economics and Management 55*(2), 175–193.

Mideksa, T. K. and S. Kallbekken (2010). The impact of climate change on the electricity market: A review. *Energy Policy 38*(7), 3579–3585.

Moretti, E. and M. Neidell (2011). Pollution, health, and avoidance behavior evidence from the ports of los angeles. *Journal of Human Resources 46*(1), 154–175.

Neidell, M. (2009). Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations. *Journal of Human Resources 44*(2), 450–478.

Nordhaus, W. D. (2010). The economics of hurricanes and implications of global warming. *Climate Change Economics 1*(01), 1–20.

Qadri, S. T. (2001). *Fire, smoke, and haze: The ASEAN response strategy.* Asian Development Bank.

Qin, Y. and H. Zhu (2018). Run away? air pollution and emigration interests in china. *Journal of Population Economics 31*(1), 235–266.

Raghunathan, R. and M. T. Pham (1999). All negative moods are not equal: Motivational influences of anxiety and sadness on decision making. *Organizational Behavior and Human Decision Processes 79*(1), 56–77.

Rosales-Rueda, M. and M. Triyana (2018). The persistent effects of early-life exposure to air pollution: Evidence from the indonesian forest fires. *Journal of Human Resources*, 0117–8497R1.

Sheldon, T. L. and C. Sankaran (2017). The impact of indonesian forest fires on singaporean pollution and health. *American Economic Review: Papers Proceedings 107*(5), 526–29.

Shimshack, J. P., M. B. Ward, and T. K. Beatty (2007). Mercury advisories: information, education, and fish consumption. *Journal of Environmental Economics and Management 53*(2), 158–179.

Smith, V. K. and J.-C. Huang (1995). Can markets value air quality? a meta-analysis of hedonic property value models. *Journal of Political Economy 103*(1), 209–227.

Viard, V. B. and S. Fu (2015). The effect of beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics 125*, 98–115.

Yang, D. (2008). Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002. *The BE Journal of Economic Analysis & Policy 8*(1).

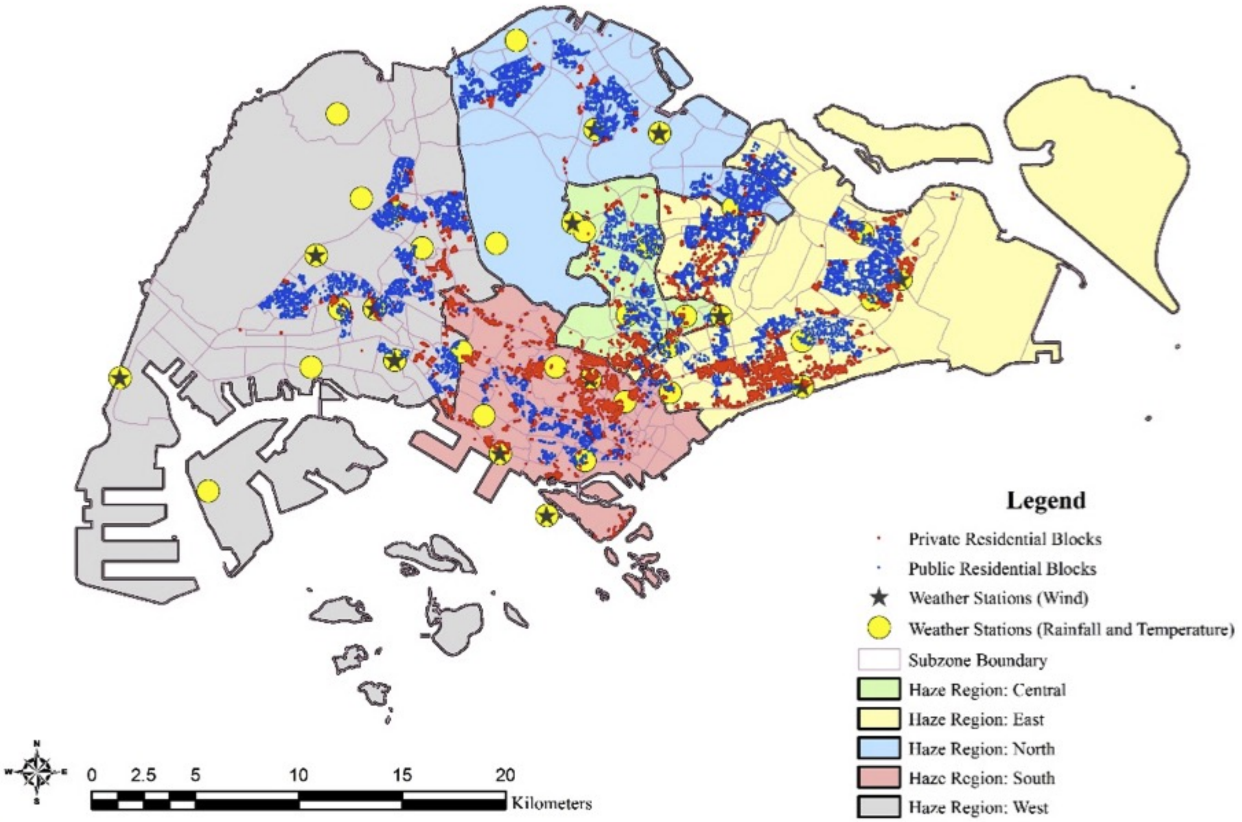
Yang, Y. (2017). Are green buildings really 'greener'? energy efficiency of green mark certified buildings in singapore. *Working Paper*.

Zhang, J. and Q. Mu (2017). Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *Journal of Environmental Economics and Management 8*(1).

Zivin, J. G. and M. Neidell (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management 58*(2), 119–128.

Zivin, J. G., M. Neidell, and W. Schlenker (2011). Water quality violations and avoidance behavior: Evidence from bottled water consumption. *American Economic Review 101*(3), 448–53.

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

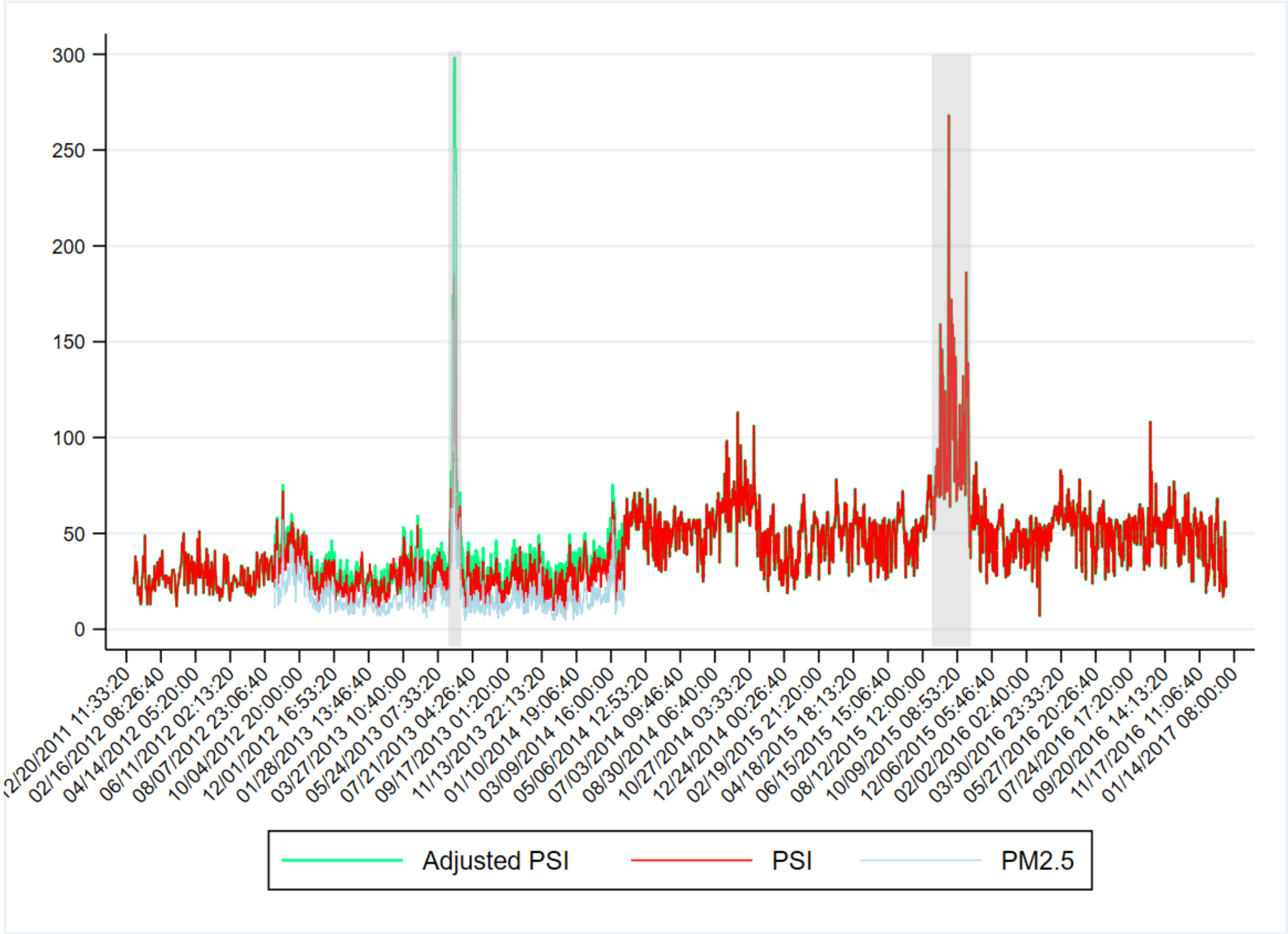


Source:
Master Plan 2014 Subzone Boundary (SIIP), Urban Redevelopment Authority, Singapore Open Data Licence, Updated on November 4, 2016.

Notes:The panel data contains monthly aggregated electricity records for 4,079 private residential buildings and 9,016 public residential buildings from Jan 2013 to Dec 2016. 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 speed data.

Figure 2: 24-Hour PSI Readings in Singapore

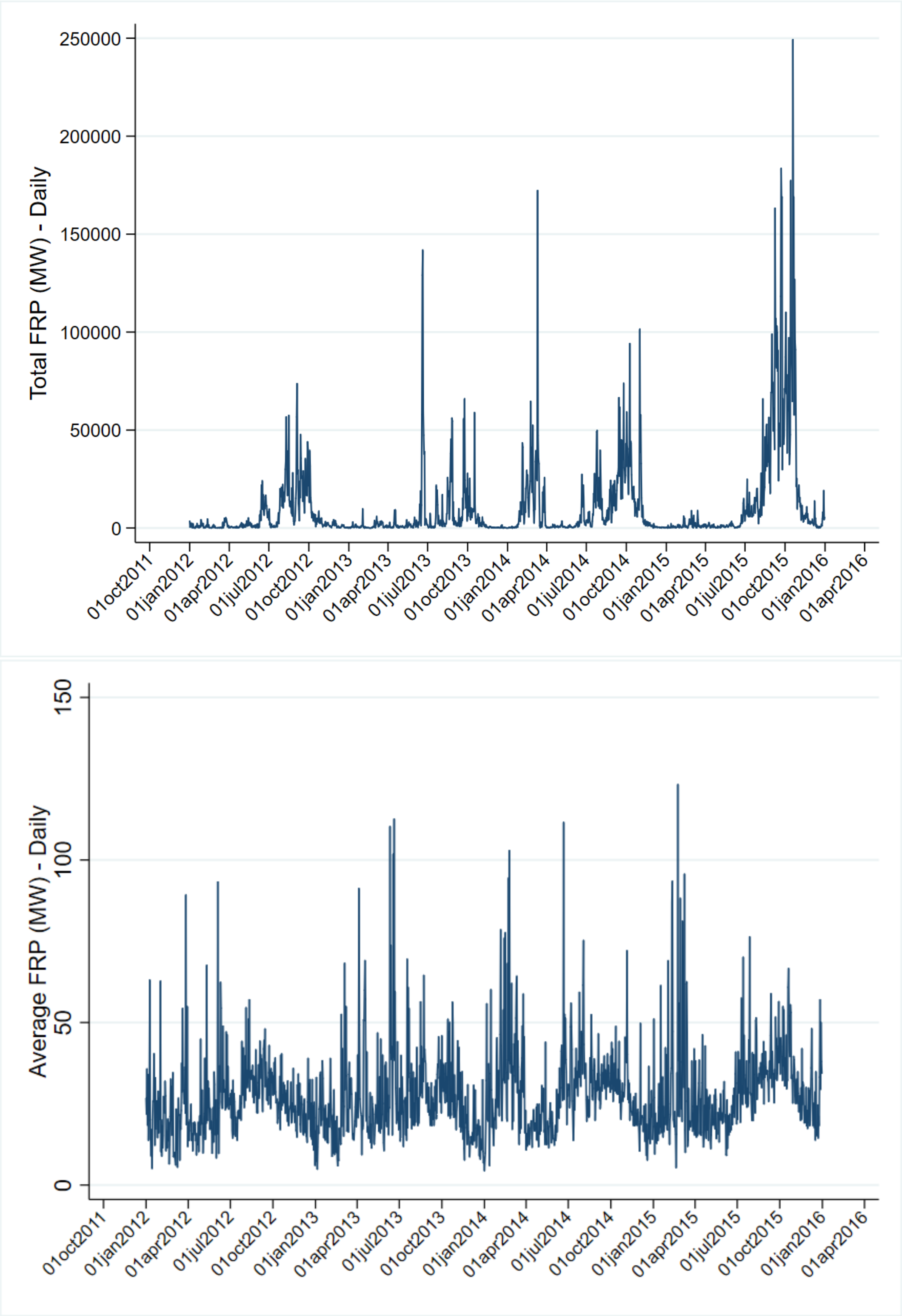
(January 1, 2012 to December 31, 2016)



Notes: This figure plots the 24-hour PSI readings from January 1, 2012 to December 31, 2016. The red line represents the variation of 24-hour PSI readings and the green line stands for adjusted 24-hour PSI measure. PM2.5 before April 1, 2014 are plotted in blue. The shaded areas stand for two severe haze shocks in June 2013 and September 2015. The width of the shaded areas represents the duration of air pollution events.

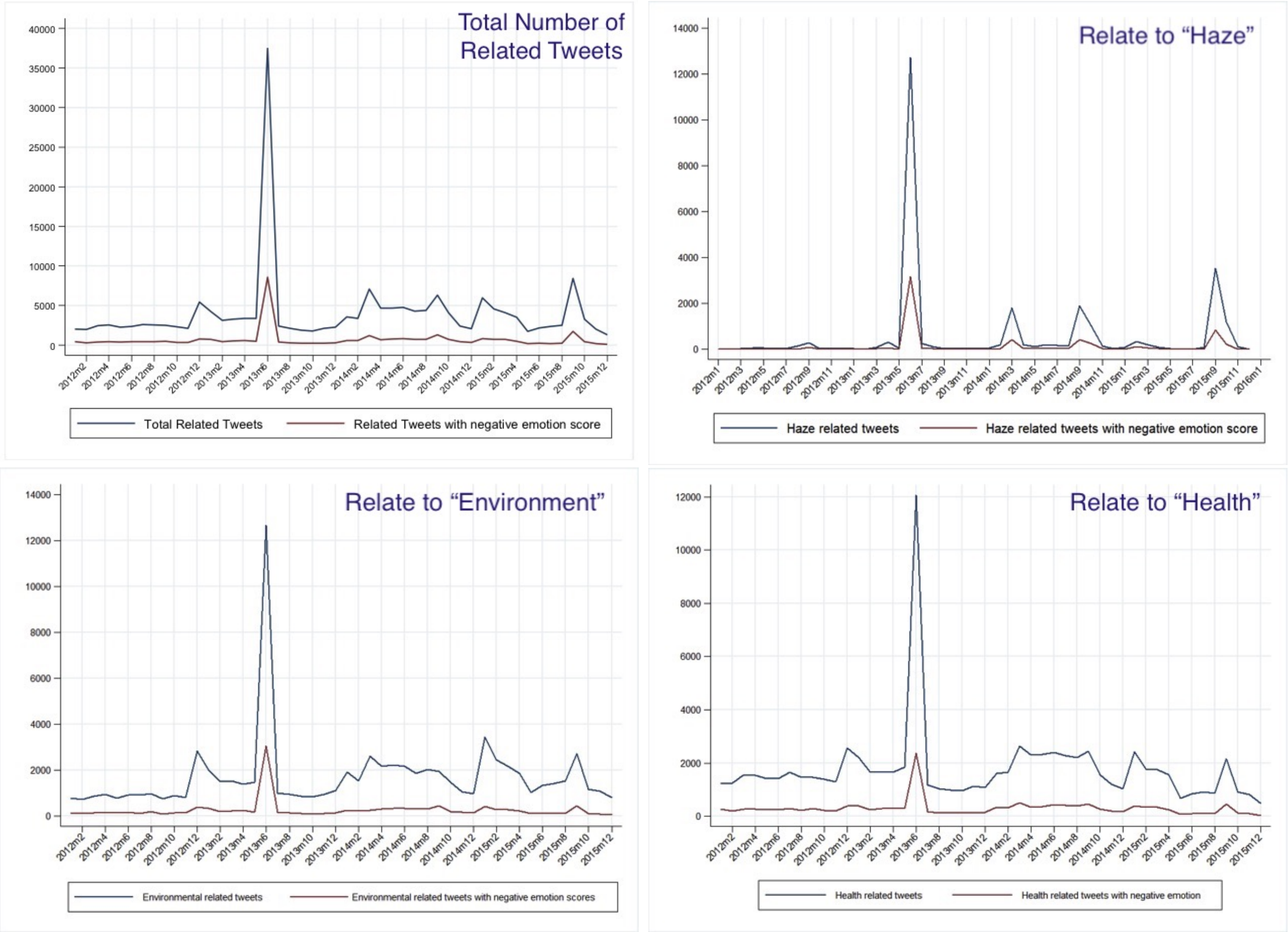
Figure 3: Daily Fire Radiative Power (FRP) in Indonesia

(January 1, 2012 to December 31, 2015)



Notes: This figure plots the daily average FRP (top graph) and the daily aggregated FRP (bottom graph) measured in megawatts (MW) in Indonesia from January 1, 2012 to December 31, 2015.

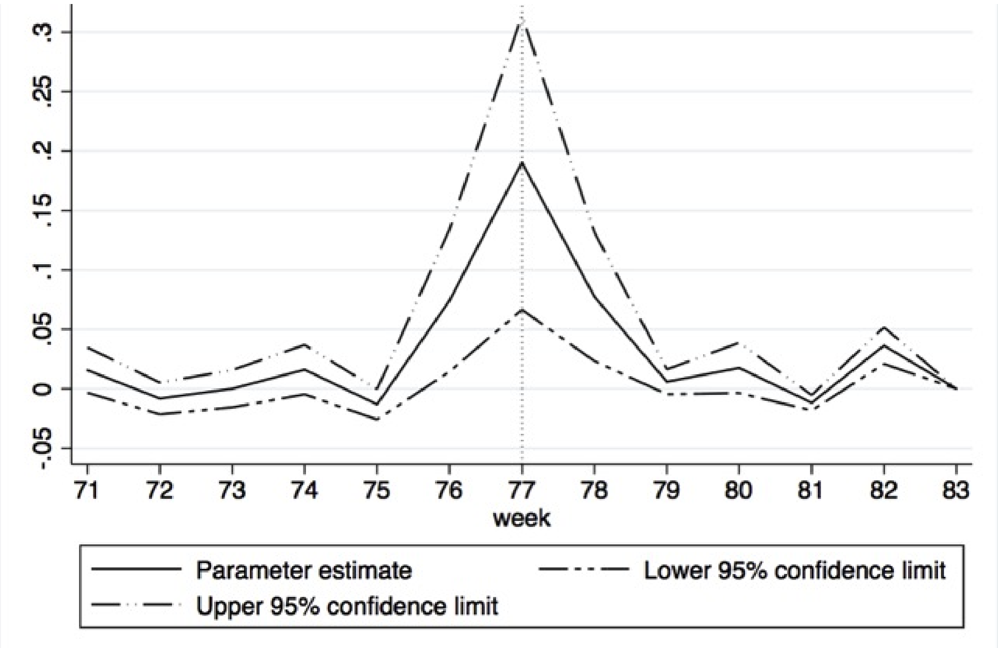
Figure 4: Monthly Haze-related Tweets by Topic from January 2012 to December 2015



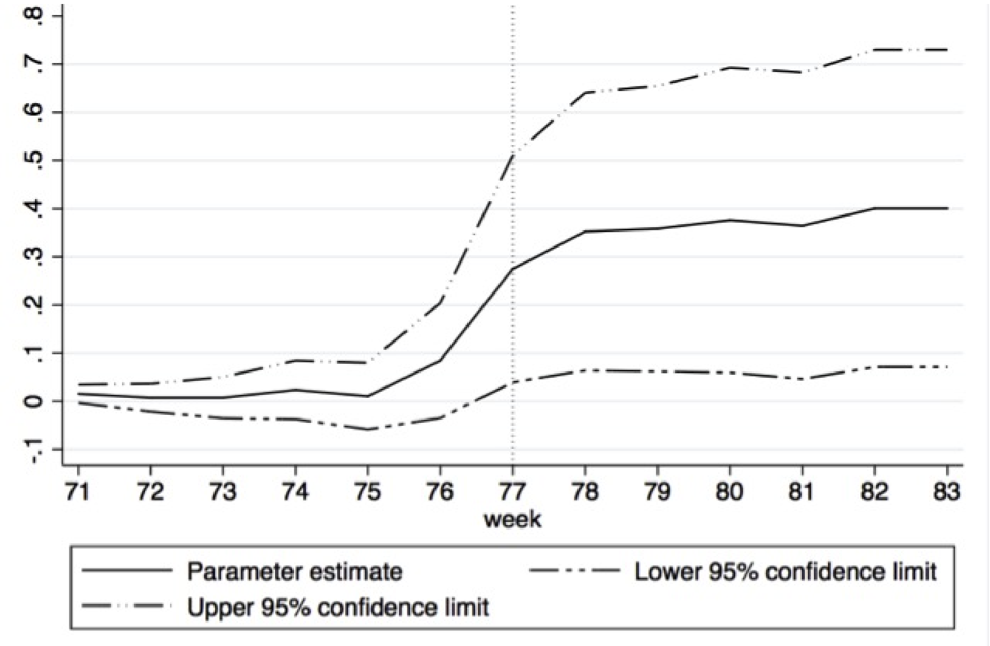
Notes: We categorize the Twitter data into three topics: haze, environment, and health. This figure shows the trends of total tweets and the three topics from 2012 to 2015. Blue lines represent the monthly tweet counts of each topic, and red lines represent tweets with negative emotion for each topic. The topic "haze" contains the following keywords: haze, hazy, NEA, air pollution, Singapore haze, PSI. The topic "environment" includes the following keywords, burn, forest, Indonesia, Malaysia, nature, smoke, Sumatra. The topic "health" includes the following keywords: asthma, breath, clinic, doctor, health, hospital, mask, N95, respiratory.

Figure 5: Short-term Haze Episodes and Estimated Water Consumption Responses

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



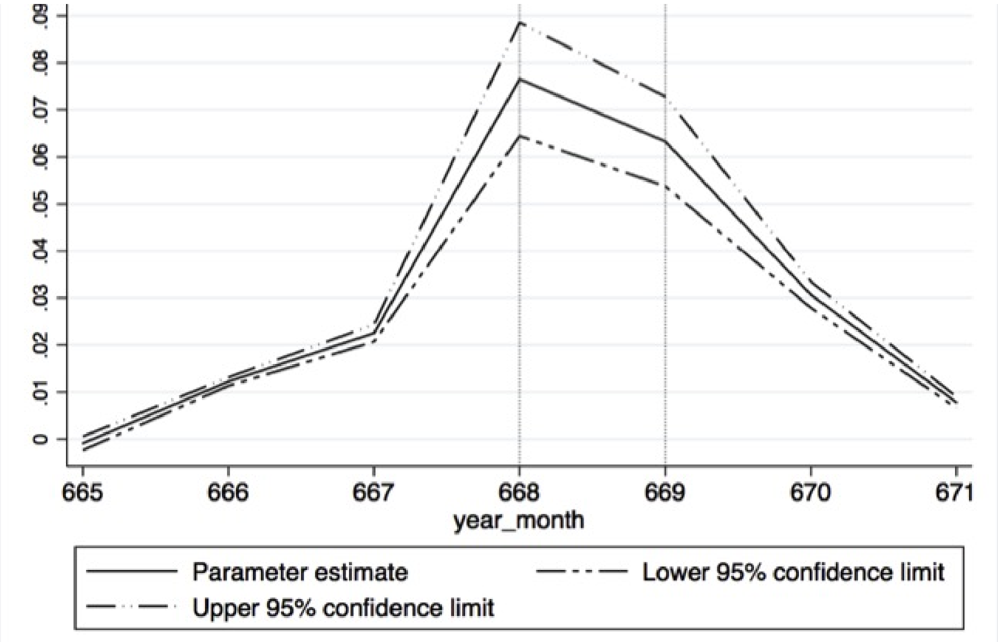
Panel B. Cumulative Water Consumption Response to Haze Episodes in Mid-June 2013



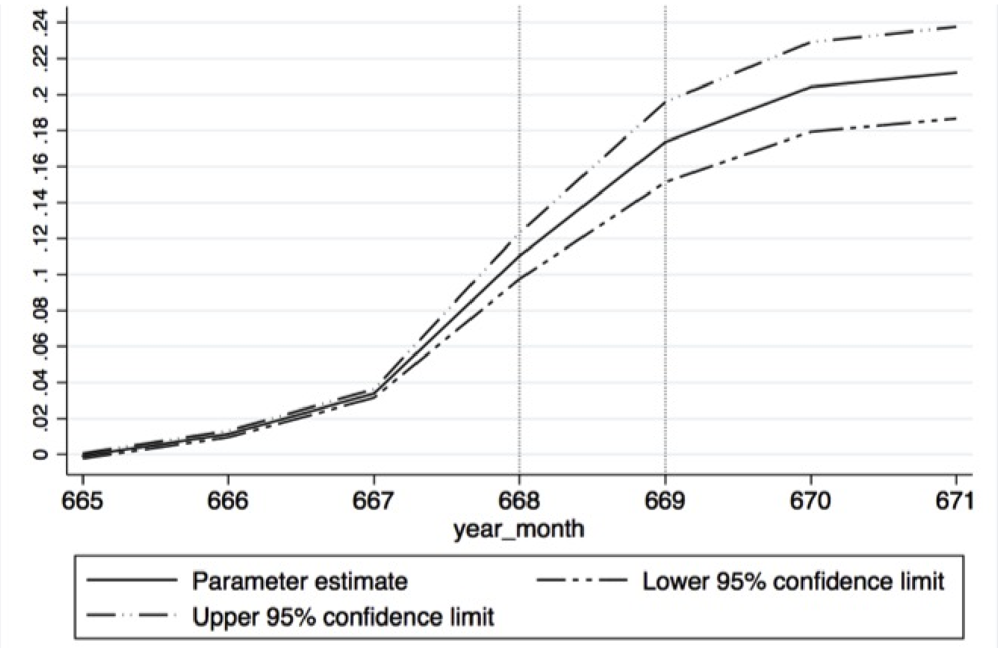
Notes: These figures plot the weekly water consumption trend. The one-week-long haze period occurring in the third week of June 2013 is identified by week "77," whereas other numbers correspond to the 13-week window before and after June 2013 (week 77). Panel A graphs the impact of the one-week air pollution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

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

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

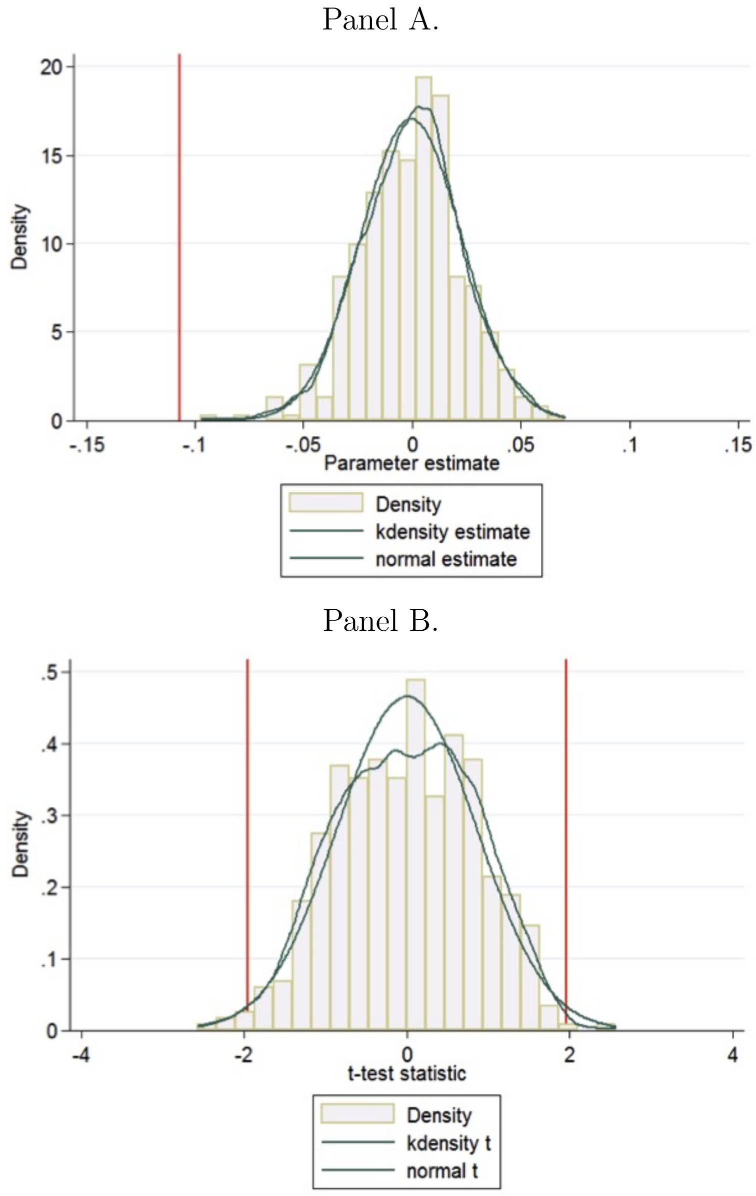


Panel B. Cumulative Electricity Consumption Response to Haze Episodes in Sept and Oct 2015



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).

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


Panel A.

Panel B.

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.

Table 1: PSI Descriptor and Health Advisory

PSI Value	PSI Descriptor	Healthy Persons	Elderly, Pregnant Women, Children, and persons with disease
0-50	Good	Normal Activities	Normal Activities
51-100	Moderate	Normal Activities	Normal Activities
101-200	Unhealthy	Reduced prolonged or strenuous outdoor physical exertion	Minimize prolonged or strenuous outdoor physical exertion
201-300	Very unhealthy	Avoid prolonged or strenuous outdoor physical exertion	Minimize outdoor activities
Above 300	Hazardous	Minimize outdoor activity	Avoid outdoor activities

Notes: Information collected from www.haze.gov.sg and https://www.moh.gov.sg

Table 2: Descriptive Statistics

Variables	Obs	Mean	Std.Dev.	Min	Max
a. Water Consumption Analysis (Household-hourly)					
Water Consumption (m^3)	8,578,992	22.244	40.158	0	998.5
Temperature (Centigrade)	27,726	28.6101	2.362	22	36
Humidity (%)	27,726	.7501	.126	.34	1
Air Pressure (hPa)	27,726	717.550	261.460	29.65	1016
Wind Speed (km/h)	26,698	9.101	5.249	1.2	35.2
FRP (MW)	35,064	6.623	18.622	0	995.267
24-hour PSI Reading	26,280	38.567	20.162	10	202
Adjusted 24-hour PSI Reading	26,280	42.520	22.992	12	298
24-hour $\mathrm{PM}_{2.5} Reading$	15,580	18.400	18.135	5	251
PSI_{change}	35,064	.438	.496	0	1
Number of Tweets (hourly)	27,600	6.997	37.048	0	3042
b. Electricity Consumption Analysis (Building-Monthly)					
Electricity Consumption (kWh)	615,421	664.405	295.374	0.026	4217.63
- Private buildings (kWh)	195,792	688.9	340.399	2.5	4217.63
- Public buildings (kWh)	419,629	652.976	271.07	0.0256	2961.46
- 1 / 2- room (kWh)	21,601	172.539	45.541	0.067	481.727
- 3-room (kWh)	113,954	286.214	61.28	0.044	875.933
- 4-room (kWh)	288,744	391.158	75.274	0.026	1,154.91
- 5 / executive room (kWh)	258,212	483.018	101.667	0.056	1,496.55
Air Pressure (hPa)	48	1009.438	0.933	1007.173	1011.266
Rainfall (mm)	48	6.121	3.499	0.014	94.6
Temperature (Centigrade)	48	28.054	0.808	25.826	29.893
Wind speed (km/h)	48	7.847	2.456	3.531	18.233
PSI Reading	48	48.701	19.509	18.560	120.438
Adjusted PSI	48	49.929	2.66	68.345	81.520
Average FRP (MW)	48	26.882	6.151	16.664	41.404
Total FRP (MW)	48	5256.624	2314.686	1599.656	11270.23
PSI_{change}	48	.693	.461	0	1
c. Electricity System Demand (Hourly)					
Electricity Demand (MW)	34,200	11077.21	1365.614	4526.68	13885

Notes: This table summarizes the observation, mean, standard deviation, and range for the key variables used in the empirical analysis. The electricity consumption sample is further sorted into private and public buildings, and public buildings includes samples with different dwelling types.

Table 3: The Impact of Haze on Household Water Consumption

Model	Panel A: Adjust PSI (1) OLS	 2) IV: $1^{st} Stage$	 (3) IV: $2^{nd} Stage$	Panel B: Include PSI_{change} (4) OLS	 (5) IV: $1^{st} Stage$	 (6) IV: $2^{nd} Stage$
ln(adjusted PSI)	0.069***		0.143*			
	(0.011)		(0.085)			
ln(PSI)				0.018***		0.119
				(0.004)		(0.074)
PSI_{change}				-0.107***	0.470***	-0.095**
				(0.010)	(0.004)	(0.045)
ln(FRP)		0.007***			0.008***	
		(0.000)			(0.000)	
ln(humidity)	-0.136***	-0.857***	0.410***	-0.021	-1.546***	0.518***
	(0.039)	(0.012)	(0.088)	(0.023)	(0.022)	(0.123)
ln(pressure)	0.002	-0.031***	0.007**	-0.010**	-0.047***	0.009**
	(0.027)	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)
ln(wind speed)	-0.023***	-0.018***	-0.001	0.007**	0.007**	-0.007
	(0.005)	(0.001)	(0.005)	(0.003)	(0.003)	(0.005)
ln(temperature)	-0.116***	0.255***	0.251***	0.015	-0.304***	0.375***
	(0.031)	(0.014)	(0.061)	(0.018)	(0.036)	(0.039)
Observations	4,505,714	4,505,714	4,503,583	4,505,714	4,505,714	4,503,583
R-squared	0.206	0.584	0.221	0.225	0.641	0.221
Fixed Effects	Year, Month, DOW, Hour, and Household Fixed Effects					

Notes: This table shows results on the average response in hourly water consumption to the changes of air pollutants. We begin by estimating an ordinary least square (OLS) model and then a 2SLS model. Columns 1 and 4 show the OLS estimates, Columns 2 and 5 show the first stage results of IV, and Columns 3 and 6 present the IV estimates. Panel A presented the results using the adjusted PSI as the pollution measure and Panel B shows the robustness check that uses an indicator variable $PSIchange_t$ and the PSI reading for the incorporation of PM2.5 into the PSI after April 1, 2014. Year, month, day, hour, and household fixed effects are included in all regressions. obust 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: The Impact of Haze on Building Electricity Consumption

	Panel A: Adjust PSI			Panel B: Include PSI$_{change}$		
Model	(1) OLS	2) IV: $1^{st} Stage$	(3) IV: $2^{nd} Stage$	(4) OLS	(5) IV: $1^{st} Stage$	(6) IV: $2^{nd} Stage$
ln(adjusted PSI)	0.037***		0.079***			
	(0.002)		(0.004)			
ln(PSI)				0.035***		0.053***
				(0.001)		(0.003)
PSI_{change}				-0.022***	0.666***	-0.030***
				(0.002)	(0.001)	(0.002)
ln(FRP)		0.454***			0.711***	
		(0.001)			(0.001)	
ln(rain)	0.013***	-0.038***	0.016***	0.017***	-0.089***	0.018***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
ln(pressure)	23.343***	281.189***	-7.500***	23.855***	-98.475***	16.158***
	(0.554)	(0.338)	(1.587)	(0.583)	(0.209)	(1.169)
ln(wind speed)	-0.011***	-0.142***	-0.017***	-0.012***	-0.148***	-0.020***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
ln(temperature)	0.970***	9.105***	0.799***	1.012***	3.701***	1.253***
	(0.026)	(0.033)	(0.058)	(0.029)	(0.019)	(0.042)
Observations	615,421	458,809	458,809	615,421	458,809	458,809
R-squared	0.821	0.656	0.167	0.821	0.828	0.169
Fixed Effects	Year, Month, Building Fixed Effects					

Notes: This table shows results on the average response in monthly electricity consumption to the changes of air pollutants. Panel A presented the results using the adjusted PSI as the pollution measure and Panel B shows the robustness check that uses an indicator variable $PSIchange_t$ and the PSI reading for the incorporation of PM2.5 into the PSI after April 1, 2014. In each Panel, we conduct both OLS and IV estimations. 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 5: Intraday and Interday Analysis

Panel A. 24-hour PSI Reading (from Jan 1, 2012 to Dec 31, 2014)

Model	(1)	2)	(3)	(4)	(5)	(6)
Testing Periods	Weekdays			Weekends		
	Full day	Daytime	Nighttime	Full day	Daytime	Nighttime
ln(PSI)	0.0132	-0.0134	0.0644***	0.0639***	0.0472*	0.0984***
	(0.0179)	(0.0188)	(0.0208)	(0.0228)	(0.0242)	(0.0287)
ln(temperature)	-0.328***	-0.358***	-0.0717	0.607***	0.534***	1.133***
	(0.103)	(0.114)	(0.129)	(0.142)	(0.170)	(0.203)
ln(humidity)	-0.401***	-0.487***	-0.0918	0.698***	0.788***	1.092***
	(0.117)	(0.135)	(0.145)	(0.169)	(0.225)	(0.229)
Pressure	-2.19e-05	-3.56e-05**	7.82e-05*	3.85e-05	-3.02e-05	0.000345***
	(1.88e-05)	(1.79e-05)	(4.15e-05)	(3.02e-05)	(2.92e-05)	(6.96e-05)
ln(Wind)	-0.00682	-0.00786	-0.0120	0.0250***	0.0249***	0.0184
	(0.00534)	(0.00571)	(0.00902)	(0.00739)	(0.00829)	(0.0142)
	(0.466)	(0.510)	(0.531)	(0.607)	(0.720)	(0.840)
Observations	4,869,739	3,076,256	1,793,483	1,926,018	1,218,263	707,755
R-squared	0.249	0.259	0.236	0.204	0.229	0.179
Fixed Effects	Year-Month, DOW, Hour, and Household Fixed Effects					

Panel B. 24-hour PM2.5 Reading (from Aug 24, 2012 to Mar 31, 2014)

Model	(7)	(8)	(9)	(10)	(11)	(12)
Testing Periods	Weekdays			Weekends		
	Full day	Daytime	Nighttime	Full day	Daytime	Nighttime
ln(PM2.5)	-0.0124	-0.0390*	0.0383*	0.0297	0.00928	0.0901***
	(0.0195)	(0.0203)	(0.0220)	(0.0230)	(0.0241)	(0.0296)
ln(temperature)	-0.311**	-0.457***	0.122	0.596***	0.562**	1.589***
	(0.146)	(0.156)	(0.178)	(0.193)	(0.225)	(0.259)
ln(humidity)	-0.311*	-0.500**	0.206	0.776***	0.769***	1.630***
	(0.167)	(0.198)	(0.200)	(0.229)	(0.282)	(0.300)
Pressure	1.15e-05	-9.35e-06	0.000126**	5.10e-05	-3.64e-05	0.000503***
	(2.29e-05)	(2.13e-05)	(4.92e-05)	(3.59e-05)	(3.57e-05)	(8.28e-05)
ln(Wind)	0.000417	0.00334	-0.0163	0.0464***	0.0516***	0.0468**
	(0.00777)	(0.00850)	(0.0118)	(0.0109)	(0.0122)	(0.0202)
Observations	2,771,901	3,076,256	1,020,909	1,099,236	1,218,263	404,112
R-squared	0.268	0.259	0.257	0.219	0.229	0.195
Fixed Effects	Year-Month, DOW, Hour, and Household Fixed Effects					

Notes: This table reports the estimation results using hourly water consumption and haze data. Panel A uses ln(24-hour PSI) as explanatory variable and Panel B uses ln (24-hour PM2.5) as explanatory variable. 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. Robust standard errors are reported in parentheses under the coefficient estimates and are clustered at the household-hour level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 6: Event Study: Effect of Haze on Household Water Consumption

Panel A: Weekdays in June 2013

Model 24-Hour PSI Cutoff	(1) 80	(2) 100	(3) 150	(4) 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)
Observations	138,680	138,680	138,680	138,680
R-squared	0.292	0.292	0.292	0.293
Fixed Effects	Year-Month, DOW, Hour, and Household Fixed Effects			

Panel B: Weekends in June 2013

Model 24-Hour PSI Cutoff	(5) 80	(6) 100	(7) 150	(8) 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)
Observations	68,753	68,753	68,753	68,753
R-squared	0.251	0.251	0.251	0.251
Fixed Effects	Year-Month, DOW, Hour, and Household Fixed Effects			

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 $24-hourPSI$ 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-hour 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

Model Topics	(1) Total Related Tweets	(2) Haze Topic	(3) Environment Topic	(4) Health Topic
ln(no. of related tweets)	0.0220***			
	(0.00802)			
ln(no. of haze tweets)		0.000998		
		(0.00454)		
ln(no. of environment tweets)			0.0160**	
			(0.00778)	
ln(no. of health tweets)				0.0309***
				(0.00860)
ln(temperature)	0.828***	0.382	0.799***	0.846***
	(0.188)	(0.240)	(0.187)	(0.188)
ln(humidity)	0.994***	0.596**	0.977***	1.021***
	(0.219)	(0.278)	(0.219)	(0.219)
Pressure	-4.01e-05	-9.61e-05*	-4.30e-05	-4.03e-05
	(3.80e-05)	(5.33e-05)	(3.80e-05)	(3.80e-05)
ln(Wind)	0.0493***	0.0679***	0.0522***	0.0485***
	(0.0170)	(0.0235)	(0.0170)	(0.0170)
Observations	361,699	204,166	361,170	361,674
R-squared	0.344	0.370	0.344	0.344
Fixed Effects	Year-Month, DOW, Hour, and Household Fixed Effects			

Notes: This table presents the relationship between the number of haze events related tweets and water consumption per day. Columns 2 to 4 explore how tweets in each topic affect water consumption. The topic "haze" contains the following keywords: haze, hazy, NEA, air pollution, Singapore haze, PSI. The topic "environment" includes the following keywords, burn, forest, Indonesia, Malaysia, nature, smoke, Sumatra. The topic "health" includes the following keywords: asthma, breath, clinic, doctor, health, hospital, mask, N95, respiratory. Household, year, month, and day of the 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-hour level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 8: The Impact of Social Awareness of Air Pollution Events on Water Consumption

Model	(1)	(2)	(3)	(4)	(5)	(6)
ln(daily max PSI)	0.0361**	0.0423***	0.0323**			
	(0.0152)	(0.0156)	(0.0159)			
ln(daily mean PSI)				0.0350***	0.0383***	0.0315**
				(0.0135)	(0.0138)	(0.0140)
ln(no. of related tweets)			0.0179**			0.0184**
			(0.00821)			(0.00813)
ln(temperature)		0.818***	0.841***		0.801***	0.829***
		(0.188)	(0.188)		(0.187)	(0.188)
ln(humidity)		0.994***	1.046***		0.977***	1.039***
		(0.221)	(0.222)		(0.220)	(0.221)
Pressure		-3.85e-05	-3.70e-05		-3.68e-05	-3.52e-05
		(3.80e-05)	(3.80e-05)		(3.80e-05)	(3.81e-05)
ln(Wind)		0.0499***	0.0494***		0.0490***	0.0487***
		(0.0170)	(0.0170)		(0.0170)	(0.0170)
Observations	361,820	361,820	361,699	361,820	361,820	361,699
R-squared	0.344	0.344	0.344	0.344	0.344	0.344
Fixed Effects	Year-Month, DOW, Hour, and Household Fixed Effects					

Notes: This table examines the impact of daily pollution measures on daily water consumption. Columns 1 to 3 use the logarithm of daily maximum PSI reading as independent variable and Columns 4 to 6 use the logarithm of daily average PSI reading as independent variable, and all coefficients are statistical significant and positive. Columns 1 and 4 explores the linear relationship between PSI and water consumption. Columns 2 and 5 include additional weather controls, such as temperature, humidity, air pressure, and wind speed. Columns 3 and 6, we further include the logarithm of total number of related tweets. Household, year, month, and day of the 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-hour level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table 9: Average Responses of Water Consumption to Haze Episode (P-score Matching)

Model	(1)	(2)	(3)	(4)
24-Hour PSI cutoff	60	70	100	150
ln(24-hour PSI)	0.0867**	0.121**	0.447	0.263
	(0.0389)	(0.0499)	(0.829)	(2.284)
Observations	156,683	69,826	2,538	2,323
R-squared	0.237	0.250	0.407	0.363
Fixed Effects	Year-Month, DOW, Hour Fixed Effects			

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 4 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-hour level. *Significant at the 10 percent level; **significant at the 5 percent level; significant at the 1 percent level.

Appendix A

Table A1. The Impact of Haze on Electricity System Demand (including both residential and commercial buildings

	Panel A: Adjust PSI			Panel B: Include PSI_{change}		
Model	(1) OLS	2) IV: $1^{st} Stage$	(3) IV: $2^{nd} Stage$	(4) OLS	(5) IV: $1^{st} Stage$	(6) IV: $2^{nd} Stage$
ln(adjusted PSI)	0.025***		0.114**			
	(0.002)		(0.055)			
ln(PSI)				0.027***		0.088**
				(0.002)		(0.041)
PSI_change				-0.012***	0.366***	-0.034**
				(0.002)	(0.010)	(0.015)
ln(FPR)		0.008***			0.010***	
		(0.002)			(0.002)	
ln(temperature)	0.385***	0.147**	0.373***	0.390***	-0.006	0.391***
	(0.016)	(0.070)	(0.019)	(0.016)	(0.068)	(0.016)
ln(wind speed)	0.011***	-0.041***	0.015***	0.011***	-0.029***	0.013***
	(0.001)	(0.005)	(0.003)	(0.001)	(0.005)	(0.002)
ln(humidity)	0.226***	-0.825***	0.301***	0.235***	-1.047***	0.299***
	(0.017)	(0.075)	(0.050)	(0.017)	(0.073)	(0.047)
ln(pressure)	0.007***	-0.021***	0.009***	0.008***	-0.040***	0.011***
	(0.001)	(0.005)	(0.002)	(0.001)	(0.005)	(0.002)
Observations	19,954	19,954	19,954	19,954	19,954	19,954
R-squared	0.661	0.604	0.608	0.662	0.659	0.639
Fixed Effects	Year, Month, Day, and Hour Fixed Effects					

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-month level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

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

Dependent Variable:	ln(Average Negative Emotion)
ln(-Average Negative Emotion Score)	0.122***
	(0.00609)
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-month level. *Significant at the 10 percent level; **significant at the 5 percent level; ***significant at the 1 percent level.

Table A3. 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	256006	29.356	256006	29.713	-0.357***
Humidity	256006	0.719	256006	0.696	0.023***
Visibility	256006	7.638	256006	7.116	0.523***
Pressure	256006	841.106	256006	846.06	-4.954
Wind Speed	256006	9.53	256006	9.321	0.209
Rain Status	256006	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 A4. Heterogeneity Tests: Race and Dwelling Type (Water Consumption)

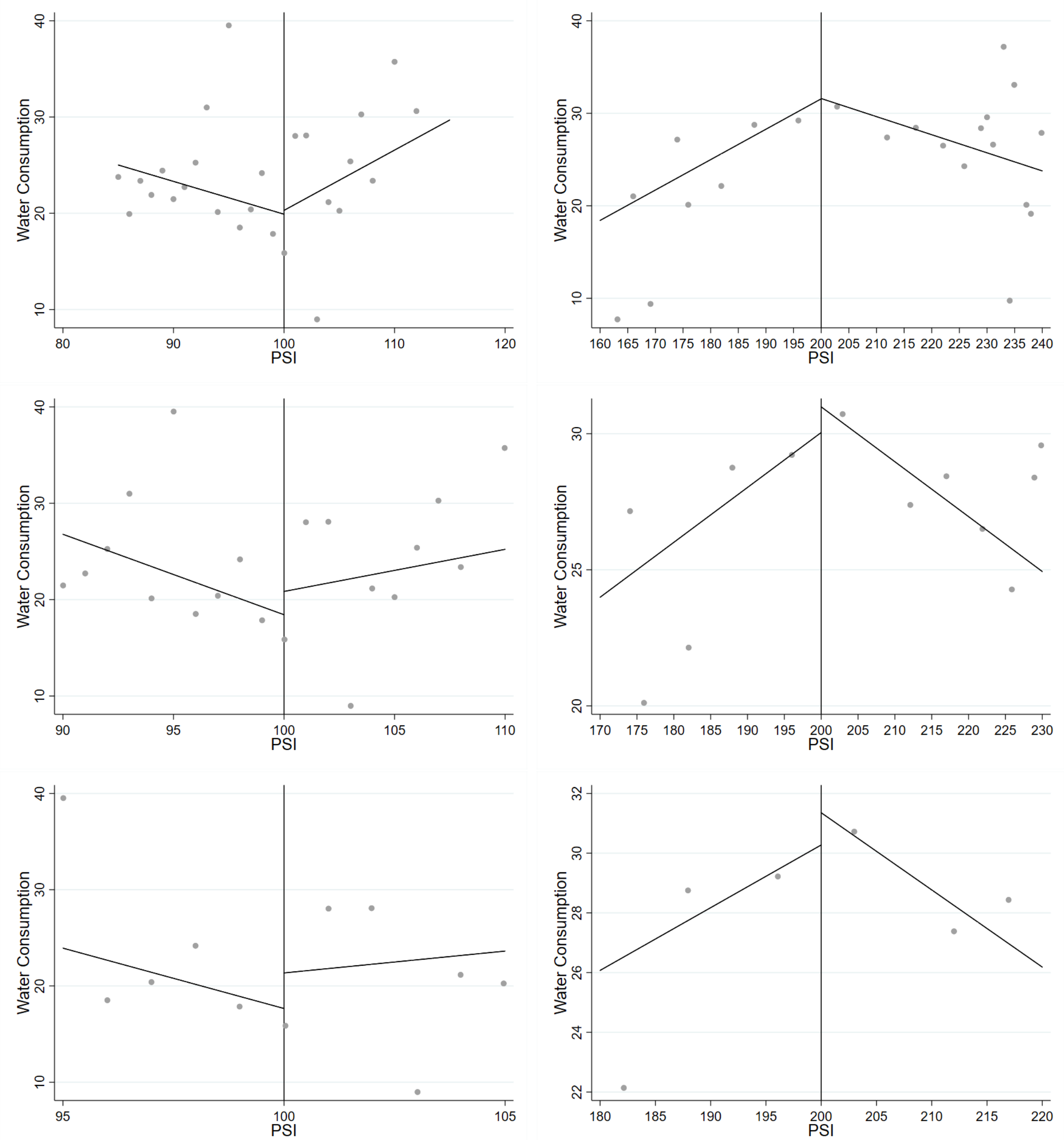
	Panel (A) Race			Panel (B) Dwelling Type		Panel (C) Floor Level				
Model	(1)	(2)	(3)	(1)	(2)	(1)	(2)	(3)	(4)	(5)
Sub-sample	Chinese	Indian	Malay	3-room	4-room	1-5	6-10	11-15	16-20	21-25
ln(PSI)	0.0490***	0.0279	0.0778***	0.0554***	0.0432***	0.0829***	0.0290*	0.0567**	0.0396*	0.0349
	(0.0104)	(0.0580)	(0.0261)	(0.0117)	(0.0137)	(0.0176)	(0.0153)	(0.0225)	(0.0205)	(0.0244)
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
Fixed Effects	Year-Month, DOW, and Hour Fixed Effects									

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-hour level. *Significant at the 10 percent level; **significant at the 5 percent level; significant at the 1 percent level.

Table A5. The Back-of-the-Envelope Calculation

1. Electricity Costs Calculation		
Monthly Households Electricity Consumption	494	Gigawatt Hours
Equal to	493,600,000	Kilowatt Hours
Current Electricity Tariff	$0.21	Per Kilowatt Hours
Additional water consumption (if one-month haze level increase by 100%)	$70,584,800	Kilowatt Hours
Additional costs (if one-month haze level increase by 100%)	$14,822,808	
Additional water consumption (if one-month haze level increase by 500%)	$352,924,000	Kilowatt Hours
Additional costs (if one-month haze level increase by 500%)	$74,114,040	
2. Water Costs Calculation		
2014 Annual Sale of Domestic Portable Water	291,200,000	Cubic Meters
Average Monthly Domestic Water Consumption	24,266,667	Cubic Meters
Current Portable Water Prices	$2.10	Per Cubic meter
Additional water consumption (if one-month haze level increase by 100%)	$1,917,067	Cubic Meters
Additional costs (if one-month haze level increase by 100%)	$4,025,840	
Additional water consumption (if one-month haze level increase by 500%)	$9,585,333	Cubic Meters
Additional costs (if one-month haze level increase by 500%)	$20,129,200	

Figure A1: Discontinuity in Water Consumption on Either Side of the Haze Warning Cutoffs



Notes: This figure plots the conditional mean of the water consumption across the haze warning thresholds (PSI=100 in the left panel and PSI=200 in right panel). Linear fitted lines are based on regressions of water consumption on baseline covariates from Jan 1, 2012 to Dec 31, 2014 on a linear polynomial in PSI reading. We plot 5 to 20 readings around the 100, and 20 to 40 readings around 200 due to limited observations around the cutoffs.

Appendix B. Computation of the Pollutant Standards Index (PSI)

The PSI is based on six pollutants particulate matter (PM10), fine particulate matter (PM2.5), sulphur dioxide (SO2), carbon monoxide (CO), ozone (O3) and nitrogen dioxide (NO2). For each pollutant, a sub-index is calculated from a segmented linear function that transforms ambient concentrations onto a scale extending from 0 through 500. The breakpoints used in defining each of the six pollutant sub-indices are listed as follows:

Index Category / $\mu g/m^3$	PSI	24-hr PM2.5	24-hr PM10	24-hr SO	8-hr CO	8-hr O3	1-hr NO
Good	0 – 50	0 – 12	0 – 50	0 – 80	0 – 5.0	0 – 118	-
Moderate	51 – 100	13 – 55	51 – 150	81 – 365	5.1 – 10.0	119 – 157	-
Unhealthy	101 – 200	56 – 150	151 – 350	366 – 800	10.1 – 17.0	158 – 235	1130
Very Unhealthy	201 – 300	151 – 250	351 – 420	801 – 1600	17.1 – 34.0	236 – 785*	1131 – 2260
Hazardous	301 – 400	251 – 350	421 – 500	1601 – 2100	34.1 – 46.0	786 – 980*	2261 – 3000
	401 – 500	351– 500	501 – 600	2101 – 2620	46.1 – 57.5	981 – 1180*	3001– 3750

Each sub-index i, is calculated by using a segmented linear function that relates pollutant concentration, X_i to sub-index value, I_i. A segmented linear function consists of straight-line segments joining discrete co-ordinates (i.e. breakpoints). For pollutant i and segment j, the co-ordinates of the jth breakpoints are represented by sub-index value Ii,j and the concentration X_{ij} giving the ordered pair (X_{ij} , I_{ij}). If the observed concentration is X_i the corresponding sub-index value Ii is calculated using the following equation over the concentration range:

$$Ii = \frac{I_{i,j+1} - I_{i,j}}{X_{i,j+1} - X_{i,j}} \cdot X_i - X_{i,j} + I_{i,j} \tag{5}$$

for $\mathrm{X}_{i,j} \leq X_i \leq X_{i,j+1}, where\mathrm{X}_i$ = Observed concentration for the i^{th} pollutant,
$I_{i,j}$ = PSI value for the i^{th} pollutant and the j^{th} breakpoint as given in the table,
$I_{i,j+1}$= PSI value for the i^{th} pollutant and the $(j^{th}+1)$ breakpoint as given in the table,
X_{ij} = Concentration for the i^{th} pollutant and j^{th} breakpoint as given in the table,
$X_{i,j+1}$= Concentration for the i^{th} pollutant and $(j^{th}+1)$ breakpoint as given in the table.

Finally, the overall index is calculated as the maximum of sub-indices: PSI = maximum ($I1$, $I2$, $I3$, $I4$, $I5$, $I6$).