Transboundary Pollution in Southeast Asia: Welfare and Avoidance Costs in Singapore from the Forest Burning in Indonesia

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typically look at reduced form impacts of changing air quality on health outcomes and do not account for averting behavior (Graff Zivin and Neidell, 2014). The first challenge is often addressed by using quasi-experiments, where researchers look at differences in health tion Standards Index (PSI), throughout the country. Since there are no major differences in the air quality in different areas in Singapore, sorting behavior is unlikely. Furthermore, since Singapore is a small country, many Singaporean residents travel within the country on a daily basis as they commute from the suburbs to the city for work and recreational activities, resulting in similar exposure to the haze. The exogenous variation of air pollution and the lack of sorting issues allow for cleaner identification than a quasi-experiment that may be subject to non-random assignments. Using polyclinic attendances for acute respiratory illnesses and acute conjunctivitis as proxies for health allow us to observe the immediate short-term effects of the Indonesian fires on the health of Singaporeans.

The full disclosure and daily reporting of the Pollution Standard Index (PSI) in Singapore promotes averting behavior amongst Singaporeans. The Singaporean government has a "Haze Page"[2] and tweets out haze advisories, a screenshot of which is shown in Appendix Figure A.1. The daily and hourly PSI as well as haze health advisories are a major area of focus on the main pages of these websites. The PSI is also reported in daily television news reports. This extensive reporting often comes with recommendations to limit outdoor activity. Given costs of S$19.9 million (US$14.7 million), indirect costs due to missed work of S$70.7 million (US$52.3 million), and increased electricity costs (between 2012-2016) of S$359.9 million (US$266.3 million), for a total cost of S$450 million (US$333 million).[3]

This paper proceeds as follows. Section 2 provides a background on forest burning in Indonesia and the related seasonal haze issues in Singapore. The data used in this paper are described in Section 3, and Section 4 reviews the empirical strategy. We present our results in Section 5. Section 6 concludes the paper.

2 Background

Between 1990 and 2015, Indonesia lost nearly 25% of its forests, mostly due to intentional burning.[4] Indonesian forest burning, primarily on the islands of Sumatra and Kalimantan, has resulted in seasonal haze episodes that last for several months in Indonesia, Malaysia, Singapore, Brunei, Southern Thailand and the Philippines (Sastry, 2002; Casson, 2002). Previous literature has identified several severe haze episodes in Southeast Asia caused by

2001 during the inter-monsoon dry seasons of February-March and July-October (Tacconi, Jotzo, and Grafton, 2006; Jones, 2006). According to NASA, the forest fires are becoming more severe over time, with the 2015 season being one of the most severe burning seasons that has been experienced by Indonesia in two decades (NASA, 2015b).

While fires have been used to clear forests to be converted for agricultural land for

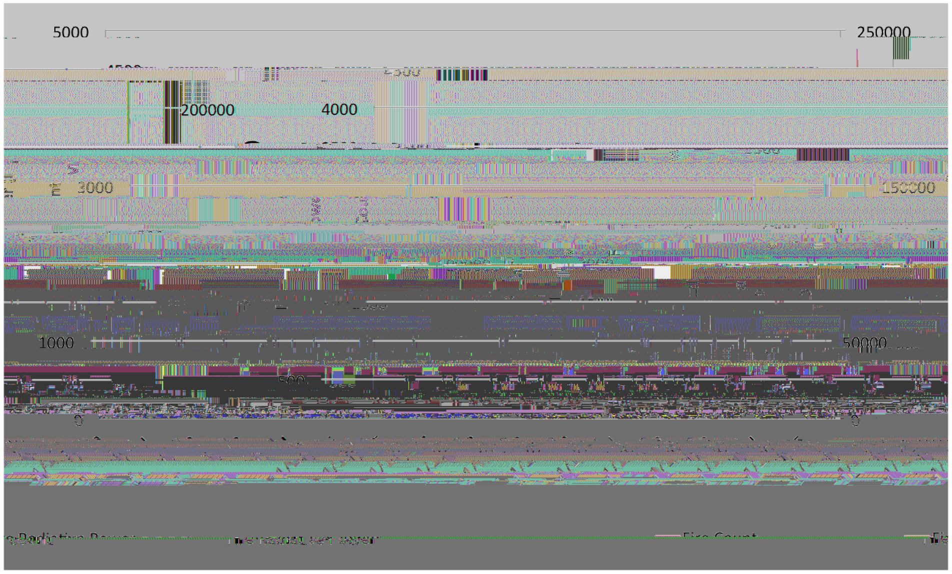
While regional discussions on the need for collaboration to combat the Indonesian for-of the compounds, how deeply they are deposited in one’s respiratory system, the duration of exposure, and the individual’s physical capacity to cope with the pollutants (Aiken, 2004;

Singaporean PSI levels (Tan, 2014). Furthermore, previous studies have not established a direct causal relationship between the forest fires in Indonesia and air quality or health outcomes in neighboring countries.

3 Data

NASA's Fire Information for Resource Management System (NASA, 2016) provides a

Figure 1: Indonesian Fires



Daily data on air quality is obtained from Singapore's National Environmental Agency (NEA, 2016). These data include daily readings of the Pollution Standards Index (PSI) from January 2010 through June 2016, as well as PM2.5 readings from September 2012 through March 2014, taken at 4pm from the north, south, east, west, and central air quality monitoring stations. The PSI is an overall measure of air quality, which gives equal weight to sulfur dioxide, particulate matter (PM10), fine particulate matter (PM2.5), nitrogen dioxide, carbon monoxide, and ozone. Prior to April of 2014, PM2.5 was reported separately and not included in the PSI.

Singapore is a small country of 277.6 square miles, about half the size of Los Angeles and two-thirds the size of New York City. As such, air quality differs little across monitoring stations, and it is likely that pollution blown over from Indonesia is well mixed over Singapore. As shown in Table 1, the correlation between the PSI of each pair of Singapore's five study utilizes the average PSI measured at 4pm across the five stations over the week as a measure of air quality. The correlation between each station's PSI and the two measures of Indonesian fires are similar, around 0.7 (ranging from 0.66 to 0.72). Thus, not only is air quality homogenous across Singapore, but air quality in all locations seems to be similarly affected by the Indonesian fires.

From Singapore's Ministry of Health we obtain weekly data from January 2010 through

Table 1: Correlation between Air Quality at Various Measurement Stations and Indonesian Fires

	FRP	Fire Count	PSI North	PSI South	PSI East	PSI West	PSI Central	PSI Average
FRP	1							
Fire Count	0.99	1						
PSI North	0.71	0.70	1					
PSI South	0.70	0.69	0.98	1				
PSI East	0.68	0.67	0.98	0.99	1			
PSI West	0.72	0.71	0.98	0.98	0.97	1		
PSI Central	0.67	0.66	0.98	0.99	0.98	0.97	1	
PSI Average	0.70	0.69	0.99	0.99	0.99	0.99	0.99	1

clinics; polyclinics see 15% of patients in the higher income group while private clinics see 85%. The Primary Care Survey Report shows that the other demographics, such as sex

Figure 2: Acute Respiratory Tract Polyclinic Attendances, Indonesian Fire Count, and Singaporean Pollution Standards Index (PSI)

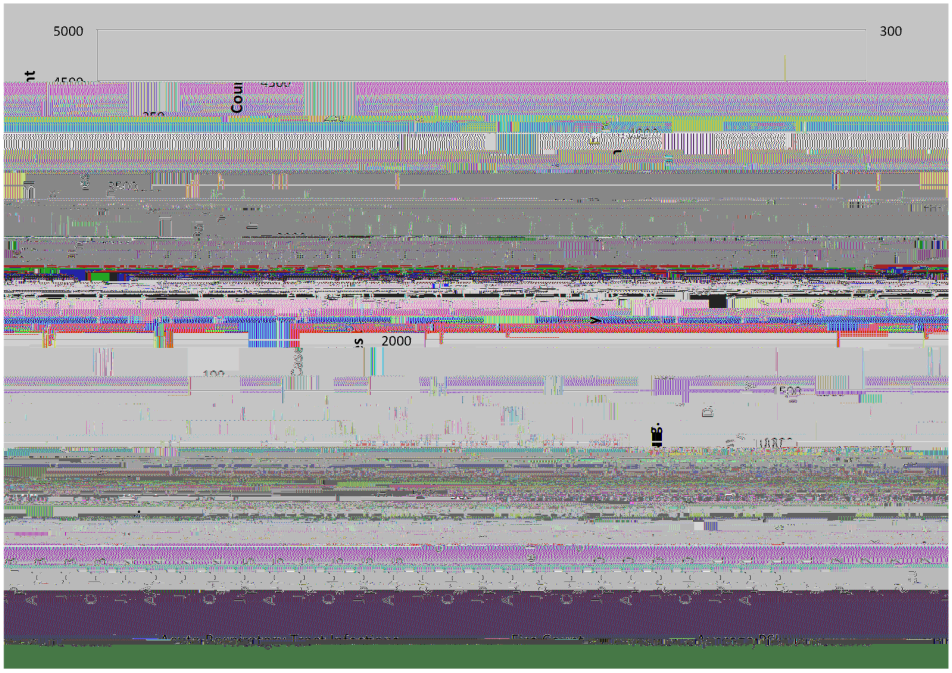


Table 2 shows the summary statistics of the key data used in our analysis. Singapore classifies a PSI under 50 as good air quality, 51-100 as moderate, 101-200 as unhealthy, 201-300 as very unhealthy, and above 300 as hazardous. On average, Singapore experienced good air quality between January 2010 and June 2016 with an average PSI at 4pm of 39.3 as shown in Table 2. However, the variation in daily air quality is large, with a minimum PSI of 10.6 and a maximum of 258.0. The daily average of fires in Indonesia from January 2010 to June 2016 was 165.3, with a minimum number of fires of 0 and a maximum of 4,750 in

Table 2: Summary Statistics

	Mean	Std. Dev.	Min	Max
Average PSI (4pm)	39.3	20.8	10.6	258.0
Daily Fire Count	165.3	352.3	0	4,750.0
Total Daily Fire Radiative Power (MW)	7,190.0	17,521.2	0	230,815.4
Daily Electricity Demand (MWh)	133,393.2	8,923.5	2723	151,068.5
Average Daily Polyclinic Visits for:				
Acute Respiratory Tract Infections	2,711.7	368.9	1,839.0	4,240.8
Acute Conjunctivitis	96.5	17.0	62.0	168.0
Acute Diarrhea	472.5	57.1	267.8	652.0

For January 2010-June 2016.

controls in our estimation. These data include daily rainfall (mm), mean temperature (°C), maximum temperature (°C), minimum temperature(°C), mean wind speed (kmh), and maximum wind speed (kmh) recorded at the Newton weather station, which is located near the center of Singapore. The weather affects the spread of the smoke from the Indonesian fires to Singapore. Weather may also impact health outcomes and polyclinic attendances. Since the polyclinic data are reported weekly, all the weather data are averaged to the weekly level for our analyses. The final dataset used in the first step of our empirical analysis includes the weekly mean of daily rainfall, mean temperature, maximum temperature, mean wind speed, and maximum wind speed as weather controls and the total weekly fire count and the from the Energy Market Authority, Singapore's power system operator, is published on Singapore's Open Data Portal (2016). We aggregate the half hourly demand to daily demand. Average daily demand is 133,393MWh.

4 Empirical Strategy

The relationship between health and pollution is often described by the following health production function (Graff Zivin and Neidell, 2014):

$$H = f(P, A, E, S), \tag{1}$$

where H is a measure of health, P is a measure of pollution, E are environmental factors such as weather, A

PSI_t: pollution standards index, a measure of air quality

H_t: health outcome (e.g., number of polyclinic attendances for ARTIs)

$fire_t$: number of fires or fire radiative power in Indonesia in week t

$fire_t \times wind_t$: interaction term between fire variable and mean wind speed

$\mathbf{weather_t}$: vector of weather variables

$diarrhea_t$: number of polyclinic attendances for acute diarrhea

$PSI\ change_t$: binary variable equal to one after the incorporation of PM2.5 into the PSI in April 2014

α_t: monthly and yearly fixed effects

In our first stage estimation (Equation 2) we regress PSI on a measure of Indonesian fires. We then use the predicted values from the first stage in the second stage (Equation 3) in order to identify the causal impact of air pollution on health outcomes. This is a more accurate approach than the approach used in existing literature of regressing health outcomes directly on air pollution indices. Regressing health on pollution does not provide a precise estimate of the impact of air pollution on health outcomes as unobserved factors, such as macroeconomic trends, can influence both health outcomes and air quality. By using fire data, we are able to estimate the Indonesian fires as an exogenous shock to Singaporean health outcomes.

Our specifications assume that Indonesian forest clearing for palm oil production is exogenous to Singapore's air quality and economy. Since the Singaporean demand for Indonesian are vastly different. Singapore's economic activities are largely driven by the service sector, whereas Indonesia's economy is largely reliant on the agricultural and industrial sectors. According to the World Bank (2016), the value added of the service sector to Singapore's GDP in 2014 was 75%, whereas the value added by the service sector to Indonesia's GDP was only 42%. Agriculture contributed 13.34% to Indonesia's GDP whereas it only contributed 0.03% to Singapore's GDP. Since the production of palm oil contributes to the agricultural sector, and the demand for palm oil is largely driven by the industrial sector, the fact that the agricultural and industrial sectors combined in Singapore contribute only 25% to Singapore's GDP indicates that trends driving the palm oil market are not likely to be correlated with the drivers of Singapore's economy.

As of April 2014, the PSI index composition changed to incorporate PM2.5. This caused a vertical upwards shift in PSI. We use an indicator variable, the PSI change, in our analyses to account for this change. Year fixed effects account for health trends and month fixed effects account for seasonality of pollution and ARTIs. We do not include year by month fixed effects because they would reduce, if not eliminate, effects from the Indonesian fire episodes, which often last a month or longer. To capture health trends not fully accounted for in the year fixed effects, we use polyclinic attendances for acute diarrhea as a proxy for general health trends in our health outcome estimations. Since diarrhea is an intestinal symptom presumably not affected by air pollution, it is sometimes used as a control variable in air pollution studies (Gordian et. al, 1996; Gajate-Garrido, 2003). For example, a patient with an upper respiratory illness as a result of a cold virus could experience diarrhea that is associated with this virus. A patient experiencing conjunctivitis as a result of a cold, rather than air pollution, might also experience symptoms of diarrhea (WebMD, 2016).

We analyze avoidance behavior separately in Section 5.2 using the following model with

$$ED_t = \theta_3 fire_t + \mathbf{weather_t \beta_6} + \alpha_t + \varepsilon_t. \tag{4}$$

5 Results

The results section proceeds as following. In Section 5.1, we analyze the impact of the Indonesian fires on the Singaporean PSI and health outcomes. In Section 5.2, we analyze the impact of the fires on residential electricity use in Singapore. Section 5.3 monetizes the estimated health and electricity impacts to assess the partial welfare effects of the Indonesian fires on Singapore.

In our analysis, we use fire radiative power (FRP) as a measure of fire intensity because its correlation with PSI and PM2.5 are somewhat higher than fire count. However, our results are similar when using fire count instead of FRP. We do not use both measures of fire because they are collinear. For ease of interpretation of the results, we transform PSI, PM2.5, FRP, ARTI, and AC by dividing by their respective standard deviations.

Table 3: First Stage Results

	(1) PSI	(2) PM2.5
FRP	1.425***	3.625**
	(0.261)	(1.418)
FRP*MeanWindSpeed	-0.0951***	-0.371**
	(0.0252)	(0.161)
PSI Change†	1.195***	
	Iti(l)7777.7d	71T6.8(-4920.2((3)0.2(7)-37840.5(.)0.1(1T6.8(Tf0.2((3)0.2(0)(195***)]T

Table 4: Second Stage Results

	(1) ARTI	(2) AC	(3) ARTI	(4) AC	(5) Chickenpox
PSI	0.351***	0.290***			0.0781
	(0.0873)	(0.0665)			(0.110)
PM2.5			0.499***	0.334***	
			(0.106)	(0.0945)	
Acute Diarrhea	0.0100***	0.00677***	0.0102***	0.00725***	0.00337**
	(0.000964)	(0.000937)	(0.00167)	(0.00172)	(0.00168)
Constant	15.46***	5.808**	20.54***	11.67**	4.973
	(2.804)	(2.503)	(3.036)	(4.842)	(3.313)
Weather Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Observations	325	325	84	84	220
R^2	0.661	0.613	0.853	0.679	0.434

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Additional lags and/or polynomials of PSI or PM2.5 are not significant and do not significantly change the above results.

a 0.33 standard deviation increase in AC cases. These results are all statistically significant at the 1% level. Acute diarrhea, the proxy for general health trends, is highly significant in

Table 5: Reduced Form Results

	(1) ARTI	(2) AC
FRP	0.668***	0.730***
	(0.222)	(0.198)

Singapore. Linear and various polynomial models are estimated to investigate the nature of the relationship between the Indonesian fires and the Singaporean energy demand. Column 3 is our preferred specification, since there appears to be a cubic relationship but higher order polynomials are not significant. Column 3 shows that a one standard deviation increase in FRP causes a 0.14 standard deviation increase (with decreasing marginal effects) in day-ahead electricity demand and a 0.11 standard deviation increase (also with decreasing marginal effects) in two day-ahead electricity demand. One- and two-day lagged FRP has a statistically significant positive impact on electricity demand in Singapore. FRP_t and FRP_{t-3} and longer lags are not significant. It takes time for the fire smoke to blow from Indonesia to Singapore, which explains why FRP_t is not significant.

Since Singapore is located by the equator, this increase in energy demand is largely caused by an increase in air conditioner use as Singaporeans choose to stay indoors. Air conditioners also help filter out air pollution. In 2013, electricity use for air conditioning accounted for the largest amount of residential energy consumed at 36.7%, with the water heater, used mostly to heat water for showers, making up 20.9% of electricity consumed by all household

Table 6: Impact of Fires (FRP) on Electricity Demand

	(1)	(2)	(3)	(4)	(5)
FRP_{t-1}	0.0293**	0.0838***	0.139**	0.102	0.0656
	(0.0114)	(0.0284)	(0.0582)	(0.0970)	(0.150)
FRP^2_{t-1}		-0.00817**	-0.0301*	-0.00640	0.0270
		(0.00354)	(0.0165)	(0.0465)	(0.117)
FRP^3_{t-1}			0.00175	-0.00266	-0.0134
			(0.00111)	(0.00762)	(0.0357)
FRP^4_{t-1}				0.000236	0.00157
				(0.000383)	(0.00441)
FRP^5_{t-1}					-5.54e-05
					(0.000184)
FRP_{t-2}	0.0228**	0.0691**	0.114**	0.131	0.213
	(0.0112)	(0.0276)	(0.0518)	(0.0855)	(0.139)
FRP^2_{t-2}		-0.00795**	-0.0268**	-0.0363	-0.123
		(0.00343)	(0.0134)	(0.0424)	(0.114)
FRP^3_{t-2}			0.00162*	0.00325	0.0329
			(0.000862)	(0.00730)	(0.0351)
FRP^4_{t-2}				-8.09e-05	-0.00393
				(0.000377)	(0.00433)
FRP^5_{t-2}					0.000164
					(0.000181)
Constant	5.235***	5.398***	5.490***	5.476***	5.485***
	(0.443)	(0.437)	(0.431)	(0.430)	(0.431)
Weather Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y
Observations	1,570	1,570	1,570	1,570	1,570
R^2	0.698	0.699	0.699	0.699	0.700

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Additional FRP lags are not significant and do not significantly change the above results.

Figure 3: Predicted PSI, with and without Fires

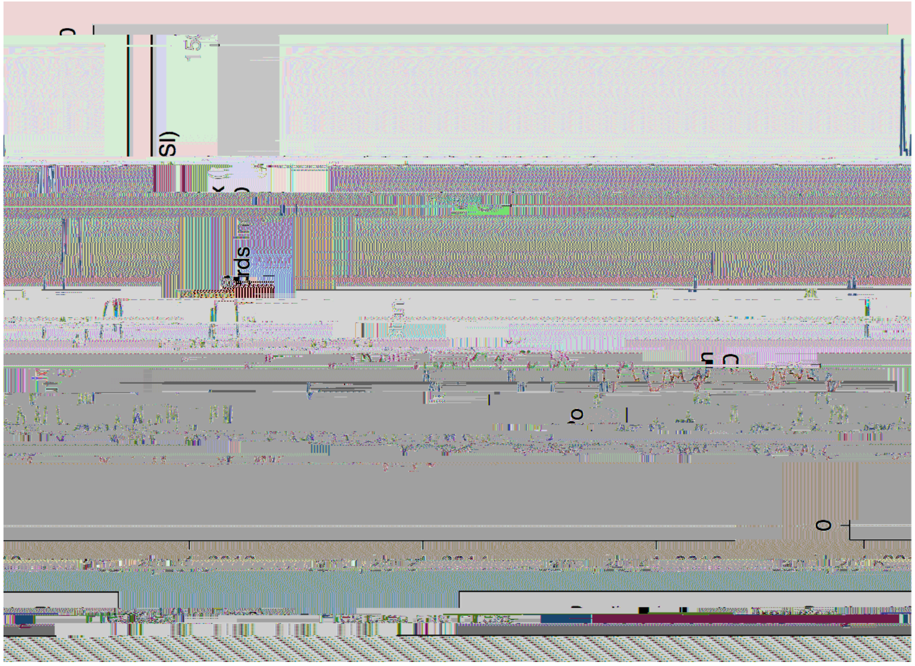
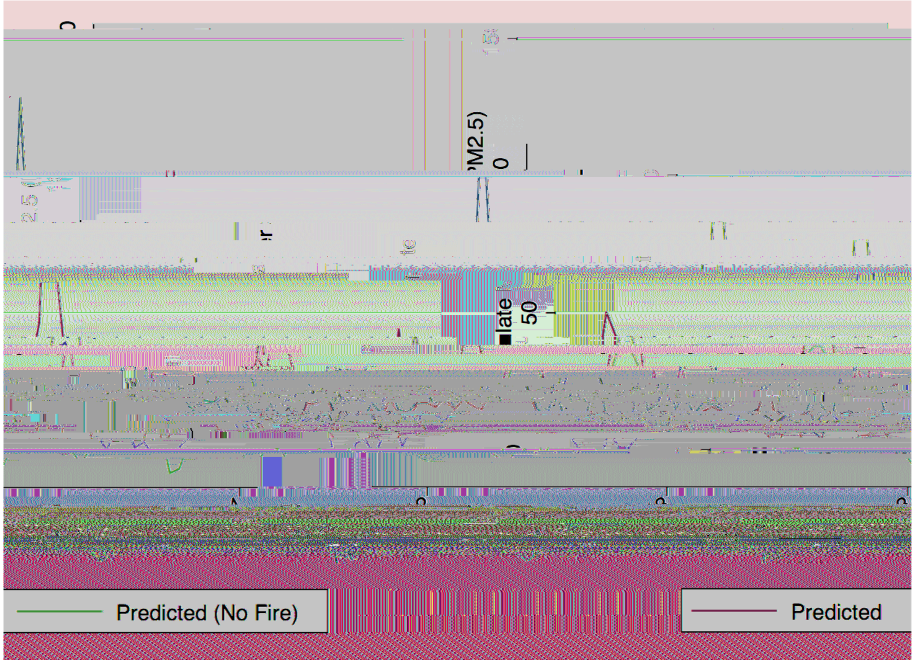


Figure 4: Predicted PM2.5, with and without Fires



were attributable to the Indonesian fires. As Table 7 shows, this percentage was lower in earlier years and has been rising over time to 4% in 2015.

Figure 6 shows weekly AC case predictions using the estimation results from Column 2 of Table 5 using both actual fire radiative power (blue) and assuming a counterfactual of no fires (red). According to the predictions in Figure 6, 1.5% of cases over this time period were attributable to the Indonesian fires. As Table 7 shows, this percentage was lower in earlier years and has been rising over time to over 3% in 2015.

Finally, using estimates from Column 3 of Table 6, we predict electricity demand using both actual fire radiative power and assuming a counterfactual of no fires. This allows us to estimate the increase in electricity demand from January 2012 to June 2016 attributable to the Indonesian fires. As shown in Table 7, the fires caused nearly a 0.9% increase in electricity demand over this time, with a maximal increase of 2.2% in 2015.

Table 8 shows the estimated direct and indirect health costs from ARTIs and AC cases, as well as the estimated costs from increased electricity use, as a result of the Indonesian

Figure 5: Predicted Acute Respiratory Tract Infections (ARTI), with and without Fires

Figure 6: Predicted Acute Conjunctivitis (AC) Cases, with and without Fires

Table 7: Percent Increases Attributable to Fires

	PSI	PM2.5	ARTI	AC	Electricity Demand

increase in electricity costs due to the Indonesian fires in the second column of the bottom panel of Table 8. These costs have also been getting bigger over time, ranging from S$35 million in 2012 to S$210 million in 2015.

We estimate the total cost of the Indonesian fires in terms of direct and indirect health costs from an increase in ARTIs and AC cases as well as increased electricity usage due to avoidance behavior to be S$450 million (US$333 million) over our sample. Since the Indonesian forest burning has become more severe, these costs have been increasing over time and were S$243 million (US$179 million) in 2015 alone, just over 0.06% of Singaporean

Table 8: Costs Attributable to Indonesian Fires

	ARTI Cases	AC Cases	ARTI + AC Direct Costs	ARTI + AC Indirect Costs	Total Health Costs (20% Popltn)
2010	2,939	106	S$152,286	S$540,920	S$693,206
2011	7,771	229	S$400,011	S$1,420,839	S$1,820,850
2012	9,711	309	S$501,033	S$1,779,668	S$2,280,701
2013	9,226	317	S$477,146	S$1,694,821	S$2,171,967
2014	18,318	567	S$944,243	S$3,353,950	S$4,298,192
2015	28,144	809	S$1,447,687	S$5,142,185	S$6,589,872
Full Sample	77,234	2,379	S$3,980,634	S$14,139,212	S$18,119,846

	Total Health Costs (100% Popltn)	Electricity Costs	Total Cost	Total Cost (USD)	Total Cost (% of GDP)
2010	S$3,466,030		S$3,466,030	$2,564,862	0.001%
2011	S$9,104,252		S$9,104,252	$6,737,147	0.002%
2012	S$11,403,505	S$35,791,494	S$47,194,998	$34,924,299	0.012%
2013	S$10,859,835	S$34,068,240	S$44,928,075	$33,246,775	0.011%
2014	S$21,490,961	S$73,598,944	S$95,089,906	$70,366,530	0.023%
2015	S$32,949,362	S$210,072,421	S$243,021,783	$179,836,120	0.061%

January 2010 through June 2016 the Indonesian fires have resulted in direct health costs of S$19.9 million (US$14.7 million) and indirect costs due to missed work of S$70.7 million (US$52.3 million).

While our study uses polyclinic attendances for acute upper respiratory tract illnesses and acute conjunctivitis, future research using other estimates of health costs, such as hospital admittances and mortality rates from haze related diseases, can provide more extensive estimates of direct costs from the Indonesian fires. Our estimates should thus be viewed as a lower bound.

Few air pollution studies examine avoidance behavior in conjunction with health costs. We estimate the increase in electricity demand induced by the fires as Singaporeans use air conditioners and stay indoors to reduce exposure to air pollution. Results indicate that a one standard deviation increase in fire radiative power increases one and two-day ahead electricity demand by more than 0.1 standard deviations. We find that from January 2012-June 2016 the Indonesian fires have resulted increased electricity costs of S$359.9 million (US$266.3 million). This estimate should also be viewed as a lower bound, since it does not include additional averting behaviors such as traveling out of the country.

The cost of this avoidance behavior is roughly four times our estimate of health costs. While both estimates are lower bounds, the relative magnitudes emphasize the importance of considering the costs of averting behavior in addition to health costs from exposure to air pollution. Negotiations on transboundary pollution policies should therefore consider not only health impacts but also behavioral responses to pollution episodes.

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B Interview with Dr. Meena Sundram, Regional Director, Jurong Polyclinics, Singapore

1. *Treatment of acute respiratory tract infections*

(c) Approximately what percentage of the patients who visit polyclinics for acute upper respiratory tract infections (and conjunctivitis) are of working age? “Approximately 40%. Children and NS [National Service] boys around 20%, 40% adults below 65. The rest would be above 65.”

4. *Polyclinics*

(a) How many polyclinics are there and how far must people travel to get there? “18 all over the island. Located very conveniently so travel would be under 20 minutes.”

(b) What are the average wait times at the polyclinics? “With an appointment can be under one hour but peak times 2-3 hrs especially Monday morning.”