Local Pollution as a Determinant of Residential Electricity Demand

Alberto Salvo*

March 28, 2020

Abstract
This study finds that a significant and hitherto ignored determinant of home energy demand is ambient particle pollution. I access longitudinal data for Singapore, a newly affluent Asian city-nation and arguably a harbinger of what is to come in the urbanizing tropics. Singapore today combines high (yet unequal) defensive capital stocks, such as residential air conditioning, with widely varying particle pollution. Overall, residential electricity demand overall grows by 1.1% when PM2.5 rises by 10 μg/m^3. I compare the pollution-electricity response to the well-known heat-electricity response, and show how it varies over the socioeconomic distribution. Local pollution control has the co-benefit of reducing electricity generation, via lower household demand, and thus mitigating carbon emissions. The observed inequality in defensive expenditure may also exacerbate health inequalities, as suggested by an exchange between epidemiologists and government.

Keywords: Energy demand, air quality, PM2.5, pollution control co-benefit, household electricity, air conditioning, defensive expenditure, rising middle class, energy inequality, health inequality, environmental justice, longitudinal study, instrumental variables

JEL codes: D12, I14, L94, O13, Q41, Q51, Q53, Q54, Q56

*Department of Economics, National University of Singapore, albertosalvo@nus.edu.sg. I am grateful to Phyllis Ang, Jeanne Cheng, Eric Fesselmeyer, Teck Hua Ho, Ivan Png, Benjamin Soo, Denis Tan, Lionel Wee, Melvin Wong, and Julian Wright for facilitating data access, as well as the organizations mentioned in the text for generously sharing their data. This research circulated previously with the title "Local Pollution Drives Global Pollution: Emissions Feedback via Residential Electricity Usage." For feedback, I thank discussants and audiences at ASSA, Duke University, Jinan University, Peking University, the Economics of Low-Carbon Markets workshop, National University of Singapore, Toulouse School of Economics, UC Davis, UC Santa Barbara, and World Congress of Environmental and Resource Economists, including Dave Keiser, Lala Ma, Céline Nauges, Dimitri Szerman and Cheng Xu. I thank Fu Ginn Cheong and Weiliang Tan for research assistance and acknowledge support from Singapore's Ministry of Education Academic Research Fund Tier 1 (R-122-000-235-112).

Data and code availability Proprietary household-level utility usage microdata can be purchased from SP Services Ltd. To allow approximate verification, the author is posting electricity and natural gas use data aggregated to usage period by two-digit zip code by dwelling type triple on the JAERE website hosted by DATAVERSE. Moreover, upon reasonable request, the microdata are available on an NUS Department of Economics (or equivalent institutional) computer to replicate all published results from the deposited computer code. The author is posting all other data, including the survey of home energy behaviors, and all code on DATAVERSE's JAERE page.

Competing financial interests The author declares no competing financial interests.

I. Introduction

Urban areas in the developing world are home to an expanding base of energy consumers (Grübler and Fisk, 2013; UN, 2014). Absent major technological or regulatory shifts, energy supply is likely to remain carbon intensive for decades (UN, 2013; IEA, 2016). Understanding what drives energy demand by the rising urban middle class is important for forecasting and influencing future emissions paths in the context of climate change (Wolfram et al., 2012; Auffhammer and Wolfram, 2014; Gertler et al., 2016). In particular, poor air quality routinely afflicts urban households in developing nations, including across Asia. Some energy-intensive durable goods, such as passenger cars and air conditioning (AC), offer households some control over exposure to ambient air pollutants. The mechanism can be both direct—e.g., one's pollutant exposure is lower in an air-filtered car cabin compared to walking to and waiting at the public bus stop—and indirect: Shutting the window at home may induce one to turn on the AC.

This study finds that a significant and hitherto ignored determinant of home energy demand is ambient particle pollution. Throughout the developing world, particle concentrations in outdoor air fluctuate in the visible range—PM2.5 between 20 and 200 $\mu g/m^3$ (Molina and Molina, 2004; WHO, 2006; Lelieveld et al., 2015).[1] Particles cause smog or haze, which is visible. The naked eye can detect differences in PM2.5 concentrations, say below 10 $\mu g/m^3$ vs. above 50 or 100 $\mu g/m^3$ (Watson, 2002). The hypothesis is that higher PM2.5 induces households to stay indoors more and, instead of naturally ventilating their home, they close their windows and use defensive capital, ranging from portable air purifiers to more powerful wall-mounted AC.[2] This defensive behavior, which is a response to ambient pollution (Kerry Smith and Desvousges, 1986; Bresnahan et al., 1997), then increases energy demand and the greenhouse gas emissions that are typically co-produced to meet that demand.

Pollution advisories recommend that the public avoid outdoor environments. These advisories are informed partly by indoor-outdoor particle concentration ratios below one for

[1] Particulate matter of diameter up to 2.5×10^{-6} m. Smaller particles are not routinely monitored, even in the US.
[2] Air purifiers consist of relatively inexpensive fans that circulate indoor air through a filter. Increasingly, AC equipment includes air-filtering capability. Bartik (1989) models optimal household defensive expenditure as a function of pollution. Bartik lists AC and air purifiers as defensive capital and notes the complexity for welfare analysis by which "air conditioners may filter air pollutants out of the interior of the home, but are also valued for cooling" (p. 123). The increased electricity expense does not capture the full welfare loss from being trapped inside to avoid bad air outside. Defensive expenditure is a key component of the marginal damage from pollution (Graff Zivin and Neidell, 2013; Deschênes et al., 2017).

typically measured microenvironments and particle size fractions such as PM2.5 (Gupta and Cheong, 2007; NEA, 2016; EPA, 2017).[3]

To identify and quantify particle pollution as a choice-based determinant of home energy demand, I access individual utility meter readings between September 2012 and December 2015 for a one-in-ten random sample of Singapore's 1.3 million households (population 5.4 million). I combine this rich microdata with concurrent PM2.5 measurements from the air-monitoring network, as well as detailed controls for temperature and other weather conditions, which may directly influence households' home energy use. The user behavior inferred here is actual, based on the individual choices of 130,000 households over time, and not hypothetical or stated. The panel design allows me to control for individual heterogeneity.

Singapore offers an ideal setting to study the role of air quality as a driver of household electricity use in the developing world. As a newly affluent city-nation, residential AC access varies widely, including saturation for apartments in condominiums and houses and low penetration for cheaper apartments. At the same time, this newly affluent nation is often exposed to developing-world levels of particle pollution. I provide two sets of estimates, based on different identifying assumptions. OLS estimates of pollution's causal impact on home energy demand assume that, conditional on controls including year and month, pollution is exogenous to unobserved household demand shocks. Such an assumption may not be as strong in Singapore as elsewhere, given the nation's relatively clean natural gas powered electricity generation. However, OLS estimates may suffer from reverse causality and I alternatively rely on an instrumental variable strategy. The main regression result is that residential electricity demand grows by 1.1% when PM2.5 rises by 10 $\mu g/m^3$, and by more among AC-saturated households.

This study links the literature on determinants of household electricity demand, particularly in the developing world,[4] with a sparse empirical literature on the defensive investments that households make in response to local air pollution. The latter literature provides either time series or cross-sectional evidence that purchases of facemasks and air purifiers increase with particle levels in China (Sun et al., 2017; Zhang and Mu, 2017; Ito and Zhang, 2019). Increased defensive expenditure by way of medication purchases, such as prescription drugs for asthmatics, has been estimated from longitudinal data for the US (Dickie and Gerking, 1991; Deschênes et al., 2017).

[3] Fig. B.5 shows substantially lower PM2.5 in indoor air-conditioned spaces relative to outdoor levels during a severe pollution episode in Singapore.

[4] Some studies focus on what drives residential AC adoption, including income, price, and temperature (Auffhammer, 2014; Auffhammer and Mansur, 2014; Rapson, 2014; Davis and Gertler, 2015).

While climate policy is often described as having "co-benefits," insofar as greenhouse gas reductions tend to be accompanied by reductions in local pollutants like PM, I document that local pollution control has its own co-benefits, by reducing electricity demand and therefore greenhouse gas (global pollutant) emissions.

In terms of mechanisms, the estimated residential electricity response to outdoor pollution shocks seems to occur along two margins of defense: (1) by households staying more at home, and (2) by PM2.5 inducing households to close windows and run defensive appliances, such as AC and air purifiers, more intensively when at home. The second margin may operate through beliefs—accurate or perceived—regarding appliances' effectiveness in abating indoor particle levels (AC, air purifiers), or simply to provide relief from indoor heat after the windows are closed, an action that impairs ventilation with the outdoor environment (AC).

Auxiliary pieces of evidence support these two margins of response. First, I review product catalogues and document that AC sellers in Singapore promote indoor air quality as an additional product attribute to cooling. The evidence indicates that firms perceive air pollution to influence AC sales. Second, I administer a survey of home energy behaviors and find that haze pollution induces sleeping with the windows closed and the AC and air purifier running at the expense of natural ventilation. The survey's findings point to appliance-intensity margin (2) above, by which appliances are used more either to purify the air or make it more comfortable.

To the extent that it is protective of one's health, the defensive behavior revealed in the microdata has environmental justice implications. Poorer households may be less willing or less able to invest in defensive capital, from windows that close to air conditioners and purifiers that to some degree abate indoor particle levels. The following critique of a recent epidemiological study illustrates how defensive expenditure can exacerbate health inequalities. A study of the health impact in Southeast Asia from September-October 2015 land fires predicted 2,200 excess deaths in Singapore (Koplitz et al., 2016). This estimate corresponds to a 73% increase over baseline mortality. Singapore's Ministry of Health responded to the study stating that the death rate was not higher in 2015 compared with 2010-2014 (CNA, 2016).[5] Following this rebuttal, one of the study's senior authors conceded that "[while] housing in [poorer] Indonesia is very well ventilated, so I don't think there is any avertive behavior that people there could have taken… In Singapore,

[5] In Appendix C, I document health responses, based on publicly available morbidity time series, which were an order of magnitude lower than Koplitz et al.'s 73% mortality increase. I estimate that Singapore polyclinic visits for disease categorized as acute upper respiratory tract infections rose by 5% during severely polluted Fall 2015.

if you close all the windows and turn on the air conditioning you get some protection" (AP, 2016). The large-scale defensive expenditure of the kind documented here helps bridge the gap between actual mortality and that estimated by Koplitz et al. from *assumed* health impact functions, which do not account for defensive behavior in a rich nation relative to its poor neighbors.

To summarize this paper's contributions, a routine and visible 10 $\mu g/m^3$ increase in PM2.5 raises aggregate electricity demand by 1%. A more severe but still in-sample PM2.5 increase to 2014 Beijing levels (98 $\mu g/m^3$) raises electricity demand—and associated carbon emissions—among the AC-saturated segment of the population by a sizable 10%. In addition to electricity, I estimate the impact of pollution on household natural gas consumption. Gas is primarily used for cooking. The pollution-cooking gas response is lower than the pollution-electricity response. I argue that the cooking gas response informs mainly on the "staying at home more" margin of defense. I find that PM2.5 has a larger *percentage* impact on electricity demand as income and AC access increase. A simple model suggests that this income differential is due to PM2.5 inducing higher-income households to turn on defensive capital when at home.[6]

A literature examines the implications of rising home energy demand, including AC, and considers income and weather as its drivers. I use longitudinal data at the scale of a leading city in Asia to include particle pollution as a key determinant, through defensive expenditure by a rising and unequal middle class. Other cities in tropical Asia experience similar climates, but lag Singapore in terms of economic development (Yuen and Kong, 2009). Only 8% of the 3 billion people living in the tropics currently have AC (Economist, 2018) compared to 76% in Singapore. My research can inform both real-time and longer-term forecasting of energy demand. Since PM2.5 and weather co-vary, my research further highlights a role for PM2.5 when assessing energy demand's weather dependence. In sum, local air quality has a global and long-lasting impact that operates via health-moderating defensive electricity demand.

II. A simple model of the heterogeneous electricity response to environmental shocks

Consider the channels through which the outdoor environment, ambient PM P and temperature T, shift the electricity consumed each period by an individual appliance j:[7]

[6] The disproportionate response by higher-income households is *not* explained by their ownership of many appliances that remain on when someone is home, irrespective of air quality; I label these "lighting capital."

[7] For brevity, here I denote pollution by P and (electricity) use by e. I thank a reviewer for suggesting a greater emphasis on "margins of response" than on "household types."

$$e_j = \mathrm{f}_j\left(t(P,T)x_j(P,T)\varphi_j(T)\right) = \beta_j t(P,T)x_j(P,T)\varphi_j(T),$$

where, for simplicity, function $\mathrm{f}_j(.)$ is a ray through the origin with slope $\beta_j > 0$, and its argument is the product of two choice variables and one physical variable: (i) t, the time the household spends at home, (ii) x_j, the fraction of time at home during which the household chooses to operate the specific appliance, and (iii) φ_j, an appliance-specific thermodynamic relationship.

Electricity consumed by some appliances—label these "lighting capital"—depends only on the time $t(P,T)$ the household spends at home, itself a function of the outdoor environment:

$$e_L = \beta_L t(P,T).$$

Here, lighting is always on when the household is at home, $x_L = 1$, and lighting efficiency is not sensitive to temperature, $\varphi_L = 1$. Environmental shocks can shift the electricity consumed by lighting through the time the household chooses to stay at home. In view of pollution advisories (NEA, 2016; EPA, 2017; MOH, 2017) and Singapore's tropical climate, I specify $t(P,T)$ to weakly increase in both P and T. With daily minimum temperatures in the 21 to 28 °C range, and daily maximum temperatures in the 25 to 35 °C range, Singapore's climate is warm but not extreme. The assumption rules out the possibility that the household stays *less* at home in response to higher P or T; this could be the case, for example, in a cold climate, or if extreme heat induced households to leave home for the air-conditioned mall.

In contrast, consider "defensive capital." These are electrical appliances that provide or are perceived to provide protection or relief from ambient PM, such as AC and air purifiers, or from heat, like AC and fans. Similarly, a household may close the windows in response to PM; a stuffy room then induces it to turn on the AC. The electricity consumed by AC is:

$$e_D = \beta_D t(P,T)x_D(P,T)\varphi_D(T).$$

Beyond the stay-home margin explained above, e_D varies with the operating-time fraction x_D, which ranges from zero (always off) to one (always on, conditional on being at home). Similar to $t(P,T)$, I specify $x_D(P,T)$ to weakly increase in both P and T. Thus, for a given ambient temperature, PM variation can shift the electricity consumed by defensive appliances through the interaction of time that the household chooses to stay at home and the chosen time fraction operating the defensive appliance. A higher stay-home time t fixing operating-time fraction x_D, or a higher x_D fixing t, raise electricity use. Ambient temperature shifts electricity demand via the same two choice margins t and x and, in addition, through a third thermodynamic channel $\varphi_D(T)$. This captures the cooling required to keep the indoor temperature at a reference level, which is an increasing function of outdoor temperature. The hotter it is outside, the higher is φ_D. Fixing the stay-home time and the operating-time fraction choices, higher outdoor temperature raises e_D.

Environmental shocks $dP > 0$ and $dT > 0$ induce electricity demand responses:

$$de_j = \beta_j \Bigg(x_j(P,T)\varphi_j(T) \underbrace{\left(\frac{\partial t(P,T)}{\partial P} dP + \frac{\partial t(P,T)}{\partial T} dT\right)}_{\text{stay home more}}$$

$$+ t(P,T)\varphi_j(T) \underbrace{\left(\frac{\partial x_j(P,T)}{\partial P} dP + \frac{\partial x_j(P,T)}{\partial T} dT\right)}_{\text{use appliance more intensively}} + t(P,T)x_j(P,T) \underbrace{\frac{\partial \varphi_j(T)}{\partial T} dT}_{\text{thermodynamic}} \Bigg).$$

It follows from the operating-time-fraction margin for defensive capital that electricity use by households holding both defensive and lighting capital (**L+D** type) responds *disproportionately* to a pollution shock $dP > 0$ relative to electricity use by households holding only lighting capital (**L only** type). To see this, write:

$$\left.\frac{de}{e}\right|_{\mathbf{L+D}\text{ type},dP>0} = \frac{de_L + de_D}{e_L + e_D} = \frac{(\beta_L + \beta_D x_D \varphi_D)\frac{\partial t}{\partial P} + \beta_D t \varphi_D \frac{\partial x_D}{\partial P}}{\beta_L + \beta_D x_D \varphi_D} \frac{dP}{t}$$

$$> \left.\frac{de}{e}\right|_{\mathbf{L\ only}\text{ type},dP>0} = \frac{de_L}{e_L} = \frac{\partial t}{\partial P}\frac{dP}{t}.$$

(Set temperature $dT = 0$, omit function arguments and recall that $x_L = \varphi_L = 1$.) For $\frac{\partial x_D}{\partial P} > 0$, a positive "income gradient" (**L+D** vs. **L only** types) to the pollution-electricity response obtains:

$$\left.\frac{de}{e}\right|_{\mathbf{L+D}\text{ type},dP>0} - \left.\frac{de}{e}\right|_{\mathbf{L\ only}\text{ type},dP>0} = \frac{\beta_D \varphi_D \frac{\partial x_D}{\partial P}}{\beta_L + \beta_D x_D \varphi_D} dP > 0$$

This result is consistent with what I find: On top of the "time at home" margin, a second "fraction of time operated" margin—such as sleeping with the AC on—leads to a disproportionate electricity demand response among households in apartment types with high AC penetration (and high income) vs. households in apartment types with lower AC penetration.

Now setting $dP = 0$, a similar logic leads to the result that electricity use by households holding both defensive and lighting capital responds disproportionately to a temperature shock $dT > 0$ relative to electricity use by households holding only lighting capital. Compared to the pollution case, the electricity response-income gradient in the temperature case exhibits an additional term, $\left(\beta_D x_D \frac{\partial \varphi_D}{\partial T} dT\right) / (\beta_L + \beta_D x_D \varphi_D)$, to account for the physical channel (cooling appliances need more power on hotter days to maintain a constant temperature):

$$\left.\frac{de}{e}\right|_{\text{L+D type},dT>0} - \left.\frac{de}{e}\right|_{\textbf{L only}\text{ type},dT>0} = \frac{\beta_D \left(\varphi_D \frac{\partial x_D}{\partial T} + x_D \frac{\partial \varphi_D}{\partial T}\right)}{\beta_L + \beta_D x_D \varphi_D} dT > 0.$$

The result is also consistent with empirical findings.

Household heterogeneity in this simple model is captured by different electrical appliance holdings. In particular, relationship $t(P, T)$ does not vary with the household type. For instance, the survey I administered shows the share of respondents dining out on a polluted day to be stable over income proxies (Fig. B.4). In principle, the response to environmental stress via the stay-home margin by households holding only lighting capital could differ compared to households with both capital holdings. This should be noted when interpreting empirical electricity responses to environmental shocks through the lens of the model.[8]

III. Institutional setting and data

I present the key data sources and in the process describe the institutional setting and the empirical design, referring to Data Appendix A for details.

Utility microdata. SP Services bills the universe of Singapore's 1.3 million housing units for their electricity and natural gas consumption from the grid (DOS, 2015; SP, 2017). I accessed an individual panel of monthly electricity and natural gas bills between September 2012 and December 2015, for a one-in-ten random sample of households. Each individual dwelling has its own metering, and its occupant holds an account with SP Services.[9] If an account holder moves to a new dwelling, a new (unlinked) account is set up and the old account is closed. I refer to an account—user by dwelling—in the microdata simply as a household.

While households receive bills every month, actual physical meter readings are typically taken once every two months (SPS, 2016). I collapse billed quantities to compute the consumption

[8] Without loss of generality, I omit a third form of capital from the model: "Refrigerator capital," held by almost all households, is typically continuously operated whether the household is at home or not, and a thermodynamic channel is present, i.e., $e_R = \beta_R \varphi_R(T)$. One can also extend the model to account for the adoption of defensive capital as a function of income, due to diminishing marginal utility of consumption on other goods.

[9] The rate of home ownership is a high nine-tenths of citizens and permanent residents, and is similar across the income distribution (Table A.2). In the case of rent, the market practice is that tenants pay for utility consumption.

rate for each period that elapses from one observed actual reading to the next.[10] Almost all usage periods in the estimation sample then have a duration of two months. Key to the empirical design is the fact that across 130,000 households, two-month periods start on different days, as the billing agent's meter-reading staff distribute their visits evenly across dwellings over time. As Fig. 1 illustrates, household i's (first) 61-day period starts on day 1, household j's 61-day period starts on day 2, so the time series variation in the data is daily. The difference in (first) billing cycle across these households consists of day 1 (in household i's cycle) minus day 62 (in household j's cycle). With household fixed effects capturing individual heterogeneity—user and dwelling characteristics including (time-averaged) income, size, composition, conservation attitudes, building/appliance characteristics—differences in energy consumption across households' billing cycles are explained by changes in daily environmental conditions, i.e., on day 1 vs. day 62 when differencing households i and j's first periods. As Auffhammer and Aroonruengsawat (2011) note, this adds to sample variation in environmental exposure.

Only 55% of sampled households purchase natural gas from the grid. Cooking is the main end use of residential gas (there is no demand for space heating). The main substitute to natural gas for residential cooking is liquefied petroleum gas (LPG), delivered in cylinders rather than from the grid. SP Services does not service the LPG market, so I do not observe LPG use.[11]

The microdata informs the dwelling's type, following standard categories, and two-digit zip code. Table A.1 describes home energy use by dwelling type. Apartments originally developed through Singapore's Housing and Development Board (HDB) account for 79% of 2.1 million household by period observations; these apartments are privately owned, and should not be confused with public housing. Apartments in condominiums, which are typically the most premium units developed by private companies, account for 16% of the sample. In densely populated Singapore, both condominium and non-condominium (HDB) apartments are often in high-rise buildings. Apartments with 5-6 rooms and in condominiums exhibit high mean electricity and natural gas use. Electricity use per person in condominium apartments averages three times that in 1-room studio apartments; in contrast, gas use per person (for cooking) is similar. Houses demand high levels of energy but account for 5% of the sample.

[10] For example, for a given household i, electricity billed in March, April, and May 2015 was based, respectively, on actual, estimated, and actual meter readings on March 5, April 5, and May 5 of 1000 kWh, 1310 kWh, and 1610 kWh, respectively. I then observe *actual* consumption of 610 kWh (1610 – 1000) over the 61-day period t that ends on May 5, 2015. Use is $610/61 = 10$ kWh/day or $10 \times 30 = 300$ kWh/month (normalized at 30 days).

[11] The purchase of LPG over natural gas is mainly due to a property lacking a connection to the natural gas grid.

Socioeconomic conditions as mediators. As is typically the case with utility data (Deschênes, 2014), the microdata do not inform on individual households' income or appliance portfolio. However, dwelling type in Singapore's housing market is observable and is informative, on average, of socioeconomic standing. Consider the socioeconomic information collected by two external household surveys. The 2012/13 Household Expenditure Survey (hereafter, HES) reports that mean annual household income per person varied widely across dwelling types, from US$ 9,300/person for 1- to 2-room apartments to US$ 68,900/person for condominium apartments (Table A.2). Access to AC at home also varied widely, from 14% among 1- to 2-room apartments to 99% among condominium apartments. Compared to AC, refrigerator penetration varied less, already reaching saturation in the lowest but two annual household expenditure bins (Fig. 2).[12] The HES did not survey air purifier ownership, but the survey I administered finds 54% of respondents with air purifiers at home.

Moreover, the Land Transport Authority's 2008 Household Interview Travel Survey (hereafter, HITS) reports dwelling type, two-digit zip code, and income (in bins), for 10,234 households across Singapore. I can then merge a measure of average income for each combination of dwelling type by zip code into the microdata. For each dwelling type by zip code pair, I compute the proportion of households with at least one member earning at least SG$ 2,500 (US$ 1,984) per month. Fig. A.5 shows that this second source of socioeconomic data again points to a clear association between dwelling type and income. Across zip codes, the median proportion of high-income households is zero for 1-room apartments, compared to at least one-half for 5- to 6-room apartments, condominiums, and houses.

Over the 2012-2015 study period, household income continued to grow smoothly. The economic environment has been stable; for example, the annual average resident unemployment rate hardly varied between 2.7 and 2.8% (MOM, 2017). The economy is open, specializing in industry (chemicals and refining) and services (maritime shipping and finance). Singapore's economy serves Asian and world markets and, in contrast to some neighboring regions, does not specialize in farm products. Industrial and commercial electricity demand jointly amount to five times residential electricity demand (Fig. A.3).

[12] For overlapping expenditure/income bins, AC penetration in Singapore is similar to that reported by Davis and Gertler (2015) for tropical municipalities in Mexico. This is consistent with the espoused view of Singapore as a harbinger of what is to come in the urbanizing tropics.

Environmental conditions as shifters. Singapore is occasionally exposed to land fires upwind and in neighboring countries, with 24-hour mean PM2.5 exceeding 300 μg/m^3 (Quah, 2002; Jayachandran, 2009; Rosales-Rueda and Triyana, 2018). Fig. A.7 shows two severe pollution episodes, one in the summer of 2013 and another in the fall of 2015. At the same time, onshore emissions from the city-state's industry, port, and roads (Velasco and Roth, 2012) contribute to routine PM2.5 variation between 10 and 32 μg/m^3. These levels are the 10th and 90th percentiles of the 2012-2015 distribution of daily means. For added perspective, PM2.5 exceeds the US primary 1-year standard of 12 μg/m^3 (EPA, 2012) on four-fifths of days and areas.[13]

Singapore's PM2.5 levels single-handedly drive the National Environment Agency's (NEA) daily Pollutant Standards Index (PSI). The NEA reports daily pollutant levels and the PSI, but issues next-day forecasts "only during periods of transboundary haze" when levels are severe (NEA, 2016). For instance, due to local emissions into a stagnant atmosphere PM2.5 in Fall 2017 reached a high 50 μg/m^3, well in the visible range, yet this did not merit an official pollution warning that might induce discontinuous changes in behavior (Mei, 2017; Tan, 2017).[14]

Singapore's tropical climate is warm and humid. There is little month-to-month variation (MSS, 2017). Daily mean temperature varies within a relatively tight range, with 10th and 90th percentiles of 26.3 and 29.1 °C, respectively. Winds are stronger during the Northeast Monsoon, from December to early March, than during the Southwest Monsoon, from June to September (Fig. A.12). Appendix A reports on the association between particle pollution and weather.

Addressing reverse causality. A long literature deals with the endogeneity of air pollution as a regressor. Here this would take the form of a feedback by which unobserved shocks to household electricity demand induce, through electricity generation, meaningful local emissions. An OLS estimator that fails to account for this endogeneity would then lead to upward biased estimates of the effect of air pollution on household electricity demand.

The previous subsection alludes to sources of pollution variation that I use to form instruments that are plausibly excluded from the household electricity demand equation. The key instrument is regional land fire intensity. Remote sensing of fire activity across Southeast Asia is available from NASA. I extract daily records of fire intensity for all individual hotspots detected

[13] Table 1 summarizes PM2.5 across Singapore's five areas. The spatial variation points to the influence of local emission sources, such as industry in the north and west.

[14] The PSI is the maximum across subindices based on increasing functions of the levels of SO_2, CO, O_3, NO_2, PM10, and PM2.5. Even during a severe and prolonged episode in September-October 2015, schools closed for only one day, and the Labor Minister vowed that "there will be no national shutdown of workplaces" (Seow, 2015).

during the study period at locations up to 2,400 km from Singapore.[15] A second instrument is based on atmospheric conditions that hinder the vertical dispersion of pollutants, sourced from NOAA.

I discuss the identifying restrictions when presenting alternative empirical models (OLS vs. 2SLS) below. I note, however, that in the specific case of Singapore I expect reverse causality to be less severe. Electricity is generated from natural gas, which burns cleaner than coal and petroleum, the prevalent fuels elsewhere in Asia. Studies for cities with coal-based electricity generation (e.g., in China, India, Indonesia) would need to rely more on an instrumental variables strategy. Singapore's open, industrial economy with a low residential share of energy use further suggest that unobserved pollution shocks originating in Singapore's residential sector are small.

IV. Econometric models of home energy demand

To explore how residential energy use responds to ambient air pollution, the baseline regression model—a separate equation for electricity use and gas use—takes the form:

$$usage_{it} = f(PM_{i\in l,t}, \lambda) + g\left(W_{i\in l,t}, \Gamma^{W}\right) + p_t\alpha_i + \delta_t + \phi_i + \varepsilon_{it}. \qquad [1]$$

An observation is an individual household i (living in location l) by period t of usage observed between two actual meter readings. The dependent variable is the log of the energy consumption rate, e.g., a household's electricity meter increases by 610 kWh during a 61-day period between two successive readings on March 5 and May 5, so I take the log of 10 kWh/day for this single 61-day observation. Regressors $f(.), g(.)$ are potentially flexible functions of concurrent environmental conditions. The key variable of interest, PM, is based on PM2.5 at location of residence l.[16] I integrate PM, weather W, and other time-varying determinants of home energy use, such as the incidence of school holidays, over each actual usage period t.

Variables PM and temperature enter the model either (i) parametrically, e.g., as the daily mean averaged over the same days in period t; or (ii) in bins for different ranges of this average level—e.g., an indicator for average PM2.5 during period t between 15 and 20 μg/m^3, another indicator for 20 to 30 μg/m^3, and so on. Fig. A.6 shows the empirical support of PM2.5 and temperature averages over household by usage period observations, ranging from 8 to 88 μg/m^3 and 26.1 to 29.1 °C. Alternatively, I specify (iii) the proportion of days in period t with daily mean

[15] Fig. A.15 shows a Singapore-centered polygon that covers much of Indonesia, Malaysia, Cambodia, and Thailand, as well as southern Myanmar, southern Laos, and southern Vietnam. Wind direction is sourced from NOAA.

[16] The analysis is robust to using PSI to proxy for air pollution. In practice, PM2.5 drives the PSI.

PM2.5 in each of different elevated ranges, i.e., the proportion of days with daily PM2.5 between 40 and 50 μg/m^3 and the proportion of days above 50 μg/m^3.

Other potential weather determinants of electricity and gas use that I control for include humidity (dew point depression), precipitation, and wind speed. I include interactions between a utility's single-block constant marginal price p_t (Fig. A.4) and indicators for the different dwelling types, thus allowing price sensitivity to vary in the cross-section, via α_i. Individual fixed effects, ϕ_i, capture unobserved heterogeneity across household accounts due to differences in behavior, family composition, and building characteristics. The ϕ_i thus subsume dwelling type by zip code. Time-varying drivers, δ_t, include year fixed effects, to capture any secular changes in the economy or the environment (though all series are stationary). To account for systematic cycles such as season, δ_t include the proportion of days in period t falling on different months of the year, days of the week, public holidays (when households may be at home), and school holidays (when households may travel).[17] λ and Γ^W are the key coefficients to be estimated, and ε_{it} is an econometric residual, interpreted as an unobserved shock to household electricity or gas use. When regression model [1] is estimated by OLS, the identifying assumption is that conditional on controls X, the residual is uncorrelated with PM. Specifically:

$$E[PM_{it}\varepsilon_{it}|X_{it}] = 0, \text{ where } X_{it} \coloneqq (W_{it}, p_t, \phi_i, \delta_t). \qquad \text{[OLS, 2]}$$

2SLS. As an alternative to OLS, I estimate model [1] via 2SLS to allow for the possible presence of omitted determinants of home energy use that may correlate with PM, in which case condition [2] would not hold. Beyond the included controls for season and trends, unobserved shocks to residential electricity demand may lead to reverse causality, from changes in emissions when electricity generation responds to demand. While 2SLS allows for this source of endogeneity, it is worth emphasizing that in Singapore, (i) households consume only 15% of the electricity supplied to an economy that is well integrated with global supply chains, responding to international demand, and growing smoothly, and (ii) the fuel mix in electricity generation is 95% cleaner-burning natural gas. Alternatively, shocks to road transport might violate assumption [2] through higher vehicle emissions that correlate with less time families spend at home and thus lower utility use. In this case, OLS estimates would be downward biased.

[17] I can flexibly allow time-varying controls to vary in the cross-section—for example, by interacting school holidays with dwelling-type indicators, as larger dwellings may be more likely to house families with children.

I specify two pollution shifters that households are unlikely to respond to directly and are thus plausibly excluded from demand equation [1]: (i) regional land fire intensity, F; and (ii) the incidence of atmospheric stagnation in Singapore, A, specifically thermal inversion from the surface to 1,000 mbar. Intuitively, only the component of PM that is predicted by the set of instruments Z (and exogenous controls X), and thus uncorrelated with omitted drivers of household utility use ε, is used to identify the causal effect of PM2.5 on utility use. This exogenous component of PM, denoted $\widehat{PM}$, is fitted in a first-stage regression:

$$PM_{i\in l,t} = F_t{}'\Delta^F + A_t{}'\Delta^A + X_{it}{}'\Delta^X + \epsilon_{it}. \qquad \text{[First stage, 3]}$$

In the first-stage regression, pollution shifts with utility demand shifters X, including time controls and surface-level weather, and instruments F and A (averages for each actual usage period t). Again, the exclusion restriction is that controlling for seasonality, home energy demand responds to land fires and a stagnant atmosphere only indirectly, through these variables' impact on pollution.[18] The 2SLS identifying assumption is:

$$E[Z_t\varepsilon_{it}|X_{it}] = 0, \text{ where } Z_t \coloneqq (F_t, A_t). \qquad \text{[2SLS, 4]}$$

Time-varying spatially weighted regional fire intensity. I spatially aggregate radiative power (in MW) across remotely sensed hotspots to construct a time-varying PM2.5 instrument that Singaporean households are unlikely to respond to directly. To capture proximity to Singapore I compute and interact two weights: (i) the inverse distance from the hotspot's location to Singapore's centroid; and (ii) the cosine of the difference between wind direction in Singapore and the initial bearing from Singapore's centroid to the hotspot's location, where the cosine weight is bounded from below by zero. Weight (ii) captures the "upwindness" vs. "downwindness" of a fire via simple vector decomposition. For example, the intensity of a fire directly upwind of Singapore receives a maximal weight of cos(0°) = 1. A fire west of Singapore when the wind blows from the south receives a weight of cos(90°) = 0, since the upwind component is zero.[19]

Early 2014 provides a good example of how weights (i) and (ii) interact to ensure instrument relevance. At that time, there were intense land fires nearby but downwind of Singapore (Sumatra, northeasterly winds), as well as upwind but far from Singapore (Cambodia). Since hotspot proximity and upwindness did not interact, weighted regional fire intensity remained low

[18] A positive temperature-altitude gradient characterizes a layer of warmer air overhead. Such thermal inversion hinders the vertical dispersion of pollutants. Households plausibly do not directly respond to shifts in atmospheric stagnation vs. turbulence (Hanna and Oliva, 2015; Arceo et al., 2016; Liu and Salvo, 2018; He et al., 2019).

[19] See the Data Appendix for a numerical example and Fig. A.16 for a visual representation.

and PM2.5 in Singapore did not spike (Figs. A.18 and A.7 respectively). In sum, I use the interaction of inverse distance and direction difference as hotspot weights, accounting for both fire proximity and the wind path of the associated emissions to Singapore.

Variants. In a robustness test, I drop atmospheric stagnation from the set of instruments Z. In another test, I add fire intensity weighted only by inverse distance to the vector of controls X, allowing nearby fires to affect household demand directly; only upwind relative to downwind fire variation is excluded from [1]. Further sensitivity analysis uses Singapore industry's electricity consumption as informative of industrial activity and emissions, which shift ambient PM2.5. To the extent that these high-frequency industry shocks correlate with aggregate income, I include them in the vector of demand controls. Alternatively, it is plausible that industry shocks originate abroad and pass through to worker wages only in the medium run, in which case I add industry shocks to the set of excluded instruments. Findings are robust to all these variations.

V. Results

Table 2 implements regression model [1] separately for electricity and natural gas. An estimation sample consists of household by usage period observations in the pooled sample trimmed at percentiles 1 and 99 of electricity or gas use by dwelling type (I later show robustness to no trimming). The key variable of interest is average PM2.5. All regressions reported in the table include flexible nonparametric controls for average temperature via granular, 0.4 °C-wide bins. As they are interesting in their own right, I report temperature effects but mostly do not discuss them. Column 1 shows OLS estimates for electricity use. A 10 μg/m^3 increase in PM2.5 exposure in the concurrent period raises electricity use by 0.010 log point, or about 1%, with standard error (se) of 0.001, two-way clustered by household and by bill-closing day.[20]

A 2SLS regression reported in column 2 yields a somewhat larger point estimate and still very high precision. This estimate employs the exclusion restriction that day-to-day home energy use does not respond to (i) regional fire intensity (as weighted by Singapore-hotspot inverse distance interacted with direction relative to wind), and (ii) atmospheric stagnation (share of days with thermal inversion), other than through these instrumental variables' effect on ambient pollution. In particular, 2SLS seeks to address possible reverse causality, which as conjectured

[20] There are 1163 clusters on bill-closing day. Adopting alternative one-way clusters at the household level yields standard errors about one-third smaller. For perspective, Auffhammer and Aroonruengsawat (2011) use one-way clusters at the household zip code level and Davis and Gertler (2015) at the municipality level.

does not appear strong in my setting. Estimates are very similar in an alternative specification with utility use, not log utility use, as the dependent variable.

Based on the subsample of households purchasing natural gas from the grid, columns 3-4 (OLS and 2SLS) show that gas demand increases by 0.9% when average PM2.5 rises by 10 $\mu g/m^3$. A possible mechanism is that as PM2.5 rises, families are more likely to cook and thus consume gas at home than to visit the local food court, a popular dining choice.[21] With regard to heat, gas demand falls by 6% for temperatures in the higher bins. Of interest in its own right, on hot days households may be less disposed to cook hot food at home, instead eating out or eating cold food.

The remaining columns of Table 2 show the environmental drivers of electricity demand based only on the subsample of households that also purchase natural gas from the grid. Comparing columns 7-8 to columns 5-6, the pollution-electricity response declines by one-tenth but remains strong when I control for concurrent gas use in the electricity use regression, e.g., +0.011 log point with gas control vs. +0.013 log point without gas control per +10 $\mu g/m^3$ PM2.5. If gas use, as a surrogate for kitchen use, is a good proxy for the time families spend at home, the evidence suggests that a key margin along which the pollution-electricity response occurs is families using their appliances differently when they are at home, such as turning on the AC or air purifier (margin x), beyond staying more at home (margin t). For example, closing the window and turning the AC on at night, as seen in the energy behavior survey presented next.

Supporting survey evidence on the use of defensive appliances. Fig. 3 (and Table B.5) report large and significant changes in stated behavior in response to haze in an online panel (N = 311) chosen to reasonably represent Singapore's population. In late 2018, I asked respondents to tick all the statements that were likely to apply to them at home on "a weekday in Singapore this October"—Appendix B shows the exact wording. Each subject was then primed with a picture of Singapore's skyline showing several landmarks shrouded in haze. While severe, the pollution that is visible in the picture is not contrived or hypothetical—it is familiar to respondents. The same question on behaviors was repeated but now applied to "a hazy weekday in Singapore in October, such as in 2015." The share of respondents stating they would "sleep with the air conditioner (air con) on" increased by one-quarter, from 51% without haze to 65% with haze. A test of equality,

[21] Food courts are ubiquitous. Situated close to residences, they tend to be in outdoor microenvironments, sheltered only from radiation and rain. Household expenditure on "food serving services" exceeds that on "food and non-alcoholic beverages" for every income quintile (DOS, 2014), underscoring the popularity of eating out (Fig. B.4).

sleep with AC during haze vs. no haze, rejects with 1% of significance. I also obtain large stated changes in behavior regarding the use of air purifiers, windows open/closed, and dining out.[22]

Heterogeneity by apartment type: Electricity response correlates with mean income and AC. I return to the microdata and implement regression model [1] on the subsample of households living in apartments. The vast majority (95%) of Singapore's households live in apartments, but income per capita and AC access are highly unequal across the different apartment types.[23] To allow for heterogeneous responses to PM2.5 and temperature, I include interactions between apartment-type indicators and each of these two environmental conditions. Since I wish to summarize the heat response in the cross-section in addition to the pollution response, temperature now enters linearly rather than in bins.[24]

Fig. 4 considers electricity use and shows estimates on PM2.5 and temperature by apartment type. As shown in the vertical axis, the heterogeneous pollution-electricity response among the different apartment types correlates with both income per capita and AC from the HES. Expressing the response relative to baseline use accounts for differences in occupancy. The pollution-electricity response exhibits positive income and AC gradients: A test of equality in the response coefficients between condominium and 1- to 2-room apartment rejects the null of equality at a 1% level of significance. The disproportionately large electricity response for apartment types with higher AC relative to those with lower AC penetration rates again suggests that, faced with poor air quality, households holding more appliances (such as AC) use these more intensively when they are at home (margin x), rather than simply households' uniformly choosing to stay more at home (margin t).[25]

The economic model above formalizes this argument. Again, lighting capital, present in every home, consumes electricity over the time the household is at home, and thus electricity use by "lighting capital only" households responds to PM2.5 only along the "time at home" margin. Households also holding defensive capital have a second choice variable: the fraction of time at home during which the defensive capital is operated. This additional "fraction of time operated"

[22] An honors thesis surveys how Singaporeans responded to a 2013 haze episode (Salvo and Tan, 2014). Table B.7, reproduced from Tan (2014), shows that in the absence of prompting, 83% of $N = 400$ respondents stated that they stayed indoors, 53% increased AC use, and 43% closed windows.
[23] Table A.2 shows little change over time, e.g., overall AC access stood at 75% in 2007/08 against 76% in 2012/13.
[24] Fig. B.1 shows that the heat response in this tropical location is indeed linear.
[25] To be clear, if a rich household runs the AC half the time when home, and a poor household none, an equal margin t across these households (and zero margin x) yields the same *percent* response to pollution.

margin for defensive capital leads to a disproportionately larger electricity demand response by households with both types of capital compared to holders of lighting capital only.

For perspective, a standard AC unit, when operated continuously over a year under typical Singapore conditions, consumes 8,600 kWh of electricity.[26] The 1.5% increase per +10 $\mu g/m^3$ PM2.5 among higher-income, AC-saturated condominium dwellers amounts to running the unit for another 10 hours per month. The manufacturer's product overview advertises that the AC unit "removes PM2.5 particles… Now you can purify the air in your home" (Panasonic, 2017). An own review of product catalogues for all AC manufacturer-series pairs sold in Singapore's residential market reveals that a majority include air quality among the advertised product attributes (Table B.6).[27] AC consumes an order of magnitude more power than a portable air purifier.

The heat-electricity response shown in the horizontal axis of Fig. 4 exhibits a qualitatively similar income gradient to the pollution-electricity response in the vertical axis. This is consistent with the notion that in response to heat and pollution alike, households with electricity-powered defensive capital operate this more intensively when at home. In the case of heat shocks, a physical margin is also present: Cooling appliances, whether operated continuously (refrigerators) or not (AC), need more power on hotter days to cool to a reference temperature. The income gradient of residential electricity's temperature dependence is then also due to thermodynamics. In contrast, the pollution-electricity response I obtain is due to behavior. Moreover, the income gradient is suggestive of the mechanism—namely, that households are more likely to use their appliances, such as AC, when PM2.5 levels rise. Overall, Fig. 4 offers a vivid depiction of the inequality in household defensive expenditure against environmental stressors.

Unlike Fig. 4's heterogeneous electricity response to environmental shocks, Fig. 5 does not show income gradients for natural gas: A test of equality for the pollution-gas response, condominium vs. 1- to 2-room apartment, fails to reject at conventional levels. Households across apartment types raise their gas use similarly in response to PM2.5. Gas-fired cooking facilities are present in almost every dwelling, and thus it is intuitive that, relative to baseline use, the shift in gas demand due to pollution is similar in the cross-section. On the other hand, the income-based differential access to AC allows households with AC to turn their units on in response to PM2.5.

[26] A Panasonic CU-XS24RKZ with 6 kW cooling capacity and a "good" energy efficiency rating (NEA, 2017).

[27] A manufacturer typically offers a model series featuring "clean air"—for example, in a wall-mounted split-system design—and a lower-end series that does not advertise indoor air quality, e.g., a window unit.

This would explain the income gradient in electricity. The horizontal axis of Fig. 5 shows that gas demand decreases with heat, and no cross-sectional pattern is evident.

Magnitude of the electricity responses associated with HITS income by local market. Table 3, columns 1-2 consider the OLS and 2SLS regressions of Table 2, columns 1-2, but replace temperature bins with a single summary measure of heat (as in Fig. 4). Columns 3-4 include interactions of the pollution and heat measures with the HITS market-level income measure, where each dwelling type by zip code defines a local market (Fig. A.5). I find that the electricity demand responses to pollution and heat alike are larger in local markets with more affluent households. The PM2.5-electricity response is about double in a market in which all households have high earners compared to a market with none (0.008+0.007 vs. 0.008 log point).

PM2.5-heat interaction, PM2.5 omitted, peak exposure. Further in Table 3, column 5 reports 2SLS estimates for a specification that adds an interaction between PM2.5 and heat. The positive effect of PM2.5 on electricity use declines as temperature rises. Intuitively, in warmer weather, households close the windows and operate the AC for heat relief irrespective of a pollution protection function. The positive PM2.5-heat interaction again points to a key role for AC.[28]

In column 6, the effect of heat on electricity use grows upon omitting PM2.5 from the electricity demand equation, i.e., a ratio of 0.0822/0.0725=1.13, or 13% higher, relative to column 1. In column 7, the effect of heat on electricity use is 35% higher upon omitting PM2.5 *and* other weather controls from the electricity demand equation. Columns 6 and 7 show the importance of controlling for pollution and other environmental conditions when assessing the temperature dependence of household electricity use.[29]

Finally, instead of specifying average PM2.5 for the usage period, column 8 includes the proportion of days in the usage period with daily mean PM2.5 in different elevated ranges (in the spirit of, e.g., Barreca et al. (2016)). Across 2.1 million household by usage period observations, the proportion of days with daily PM2.5 in excess of 50 μg/m^3 exhibits a range of zero to 0.83 (i.e., four-fifths of days). Relative to a reference category in which daily PM2.5 stays below 40

---

[28] To interpret the point estimates in column 5, a +10 μg/m^3 rise in average PM2.5 raises electricity use by (i) $0.6001 - 0.0207 \times 27 = 0.041$ log point at an average temperature of 27 °C, and (ii) $.6001 - 0.0207 \times 28 = 0.021$ log point at an average temperature of 28 °C (the in-sample average temperature range is 26.1-29.1 °C).

[29] The coefficient on temperature in column 1 invariably grows on progressively dropping PM2.5, dew point depression, precipitation, and wind speed from the model, from 0.073 to 0.082 to 0.084 to 0.093 to 0.098 log point. How heat affects residential electricity use is examined by Sailor and Pavlova (2003), Mideksa and Kallbekken (2010), Auffhammer and Aroonruengsawat (2011), Deschênes and Greenstone (2011), Auffhammer and Mansur (2014), Salvo (2018), and Li et al. (2019).

μg/m^3 throughout, electricity use is estimated to grow by 0.098 log point, or +10.3%, during a usage period of severe PM2.5 throughout, defined here as over 50 μg/m^3.

Robustness. Table B.1 reports robustness tests of estimated electricity responses: (i) standard errors two-way clustered on household and usage period (with 5540 unique periods compared with 1163 clusters on bill-closing day); (ii) controlling for possible omitted drivers of residential electricity use such as labor market conditions, e.g., average wage interacted with dwelling type; (iii) allowing for heterogeneous trends, by dwelling type × zip code (360 local markets); (iv) controlling for all weather conditions entering via granular bins;[30] (v) controlling for solar radiation; and (vi) varying the identifying assumptions. Table B.2 reports on the first stage of 2SLS models with alternative identifying restrictions. Table B.3 shows robustness to collapsing the data to area by usage period. Table B.4 adds pollution in the next billing cycle as a regressor.

Fig. B.1 reports electricity responses to pollution and heat for specifications in which these environmental stressors both enter nonlinearly, whether through bins or through splines. Besides the pooled sample, I show estimates implemented separately by dwelling type subsample. Over the range of environmental exposure, effects appear linear, at least judged by the OLS estimator.

VI. Conclusion and policy implications

This research, conducted at the scale of a leading Asian city, quantifies and highlights another compelling reason why "particulate matter matters" (Dominici et al., 2014): PM control brings climate co-benefits. With 40% of the developing world's population living in the tropics, local air pollution significantly raises both (1) households' defensive electricity expenditure, and (2) greenhouse gas emissions that are co-produced in supplying that electricity. For instance, urban populations in India and Indonesia suffer from poor air quality and are fast-adopting AC, and these nations' power generation is set to remain coal-intensive for decades (Koplitz et al., 2017). The behavior observed for newly affluent Singapore in which AC is widely available—including advertising by AC sellers (Table B.6)—suggests another reason why AC may be valued by rising middle classes routinely exposed to particle pollution, thus leading to higher and faster adoption. Lower electricity demand and the reduced global pollutant emissions associated with electricity generation are thus co-benefits of policies to abate ambient particle levels, to which households' defensive expenditures respond.

[30] Estimates on these bins are credible, e.g., electricity demand increases in humidity and decreases in wind speed.

Table 4 offers a thought experiment to illustrate the climate co-benefit of local pollution control. I employ jointly fitted PM2.5 and temperature splines (Fig. B.1) to predict Singapore's residential electricity consumption in 2014 had Singapore's households hypothetically been exposed to the same PM2.5 level as that concurrently recorded day by day in Beijing (2014 mean = 98 $\mu g/m^3$ against Singapore's 2014 mean = 19 $\mu g/m^3$). This prediction is largely within sample, since the 2012-2015 estimation sample included daily PM2.5 realizations up to 300 $\mu g/m^3$. Compared to actual air quality, and ignoring further AC adoption and differences in PM composition, a household's electricity use under the counterfactual scenario would rise by an average 31 kWh/month (+7% over mean actual use), and by double this quantity among higher-income, AC-saturated households in condominium apartments (+60 kWh/month or +10% over mean condominium use).

To emphasize, were the AC-saturated households among Singapore's population exposed to one year of Beijing's air, their electricity demand would rise by 10% (95% CI = [8%, 12%]), with annual electricity expenditure increases of US$ 160 per household. Across Singapore's 1.3 million households over 1 year, electricity expenditure and CO_2 emissions would rise by US$ 110 million and 220 thousand tons, respectively. Counterfactual CO_2 emissions would be higher still—about double—if Singapore's electricity grid used coal, the predominant fuel in Asia (and reverse causality might be stronger). Table 4 frames the pollution-electricity response in the context of the heat-electricity response. Exposing Singapore in 2014 to PM2.5 concurrently recorded in Beijing would have an impact on residential electricity use similar to making Singapore hotter by 1 °C.[31] Another degree of warming over preindustrial levels is widely forecast by 2060 even if the Paris Agreement were met.

The inferred residential electricity response to rising PM2.5—which is (i) disproportionately stronger than the cooking gas response and (ii) disproportionately stronger among apartment types with high AC access and in markets with higher incomes—is suggestive of the underlying mechanisms. Beyond households' staying at home more to mitigate the pollution impact, more residential AC units and air purifiers power up when pollution rises. My survey of home energy behaviors, coupled with evidence that firms perceive pollution to influence AC sales,

[31] Table 4 (and Figs. B.2 and B.3) offer further counterfactual pollution scenarios, with Singapore exposed to air recorded in Asian cities with climates closer to Singapore's, namely Kolkata (2016 mean PM2.5 = 84 $\mu g/m^3$) and Dhaka (2017 mean PM2.5 = 80 $\mu g/m^3$).

support these mechanisms. Future research can use hourly appliance-level electricity consumption to examine the linkages reported here.

The observational data point to substantial inequality in defensive expenditure even within a city-nation. Fig. 4, which compares the pollution-electricity response to the well-known heat-electricity response, vividly illustrates this inequity. A 10 $\mu g/m^3$ increase in PM2.5 is met by households in condominium apartments with a 1.5% increase in electricity consumption, compared with a statistically distinct 0.75% increase by households in 1- to 2-room apartments.

Future work can also examine the effective health protection from households' actions, both within and across locations. This will further inform the debate surrounding the 2,200 excess deaths calculated from assumed health impact functions—which presumably failed to account for defensive expenditure—for the 2015 transboundary haze episode (AP, 2016; Koplitz et al., 2016). As described in the introduction, the estimate was refuted by Singapore's government (CNA, 2016). The use of defensive capital, as inferred here from residential electricity demand, might help bridge the gap between the 2,200 estimate and observed mortality from actual exposure, per the government's rebuttal. That wealthier and more educated households are better equipped to invest in and use defensive capital has important environmental justice implications, given the high particle levels observed in developing countries (Lelieveld et al., 2015; Marlier et al., 2016; Banzhaf et al., 2019). To the extent that AC affords or enables protection from ambient PM (Fig. B.5) and that PM and temperature are associated, it is conceivable that declining PM exposure explains a portion of the decline in the temperature-mortality response in the US, via residential AC diffusion (Barreca et al., 2016); this issue warrants investigation. The household behavior identified here may plausibly extend beyond the adoption of energy-intensive durables at home, for example, with households choosing the indoor air of a passenger car cabin or a shopping mall over exposure to pollution at the bus stop or park. The extent to which concerns over air quality are driving fast-rising demand for energy-intensive cars and shopping malls in the developing world seems worth examining (Wolfram, 2014).

References.

AP (2016). 'Study Estimates 100,000 Deaths from Indonesia Haze', *Associated Press*, vol. **September 19**.

Arceo, Eva, Rema Hanna and Paulina Oliva (2016). 'Does the Effect of Pollution on Infant Mortality Differ Between Developing and Developed Countries? Evidence from Mexico City', *The Economic Journal*, vol. **126**(**591**), pp. 257-280.

Auffhammer, Maximilian (2014). 'Cooling China: The Weather Dependence of Air Conditioner Adoption', *Front. Econ. China*, vol. **9**(**1**), pp. 70-84.

Auffhammer, Maximilian and Anin Aroonruengsawat (2011). 'Simulating the Impacts of Climate Change, Prices and Population on California's Residential Electricity Consumption', *Climatic Change*, vol. **109**(**1**), pp. 191-210.

Auffhammer, Maximilian and Erin T. Mansur (2014). 'Measuring Climatic Impacts on Energy Consumption: A Review of the Empirical Literature', *Energy Economics*, vol. **46**, pp. 522-530.

Auffhammer, Maximilian and Catherine D. Wolfram (2014). 'Powering Up China: Income Distributions and Residential Electricity Consumption', *American Economic Review*, vol. **104**(**5**), pp. 575-580.

Banzhaf, Spencer, Lala Ma and Christopher Timmins (2019). 'Environmental Justice: The Economics of Race, Place, and Pollution', *Journal of Economic Perspectives*, vol. **33**(**1**), pp. 185-208.

Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone and Joseph S. Shapiro (2016). 'Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century', *Journal of Political Economy*, vol. **124**(**1**), pp. 105-159.

Bartik, Tim J. (1989). 'Evaluating the Benefits of Non-marginal Reductions in Pollution using Information on Defensive Expenditures', *Journal of Environmental Economics and Management*, vol. **15**(**1**), pp. 111-127.

Bresnahan, Brian W., Mark Dickie and Shelby Gerking (1997). 'Averting Behavior and Urban Air Pollution', *Land Economics*, vol. **73**(**3**), pp. 340-357.

CNA (2016). 'Study on Haze-Related Deaths 'Not Reflective of Actual Situation': Ministry of Health', *Channel News Asia*, vol. **September 19**.

Davis, Lucas W. and Paul J. Gertler (2015). 'Contribution of Air Conditioning Adoption to Future Energy Use under Global Warming', *Proceedings of the National Academy of Sciences*, vol. **112**(**19**), pp. 5962-5967.

Deschênes, Olivier (2014). 'Temperature, Human Health, and Adaptation: A Review of the Empirical Literature', *Energy Economics*, vol. **46**, pp. 606-619.

Deschênes, Olivier and Michael Greenstone (2011). 'Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US', *American Economic Journal: Applied Economics*, vol. **3**(**4**), pp. 152-185.

Deschênes, Olivier, Michael Greenstone and Joseph Shapiro (2017). 'Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program and Ozone Reductions', *American Economic Review*, vol. **107**(**10**), pp. 2958-2989.

Dickie, Mark and Shelby Gerking (1991). 'Willingness to Pay for Ozone Control: Inferences from the Demand for Medical Care', *Journal of Environmental Economics and Management*, vol. **21**(**1**), pp. 1-16.

Dominici, Francesca, Michael Greenstone and Cass R. Sunstein (2014). 'Particulate Matter Matters', *Science*, vol. **344**(**6181**), pp. 257-259.

DOS (2014). *Report on the 2012/13 Household Expenditure Survey* Singapore: Department of Statistics, Singapore.

DOS (2015). *Singapore in Figures*, Singapore: Department of Statistics, Singapore.

Economist (2018). 'Air-conditioners do great good, but at a high environmental cost', *The Economist*, vol. **August 25**.

EPA (2012). *The National Ambient Air Quality Standards for Particle Pollution*, Research Triangle Park: U.S. Environmental Protection Agency.

EPA (2017). *Air Quality Guide for Particle Pollution*, Washington, D.C.: US Environmental Protection Agency.

Gertler, Paul J., Orie Shelef, Catherine D. Wolfram and Alan Fuchs (2016). 'The Demand for Energy-Using Assets among the World's Rising Middle Classes', *American Economic Review*, vol. **106**(**6**), pp. 1366-1401.

Graff Zivin, Joshua and Matthew Neidell (2013). 'Environment, Health, and Human Capital', *Journal of Economic Literature*, vol. **51**(**3**), pp. 689-730.

Grübler, Arnulf and David J. Fisk (2013). *Energizing Sustainable Cities: Assessing Urban Energy*, New York: Routledge.

Gupta, Abhishek and K. W. David Cheong (2007). 'Physical Characterization of Particulate Matter and Ambient Meteorological Parameters at Different Indoor–Outdoor Locations in Singapore', *Building and Environment*, vol. **42**(**1**), pp. 237-245.

Hanna, Rema and Paulina Oliva (2015). 'The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City', *Journal of Public Economics*, vol. **122**, pp. 68-79.

He, Jiaxiu, Haoming Liu and Alberto Salvo (2019). 'Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China', *American Economic Journal: Applied Economics*, vol. **11**(**1**), pp. 1-31.

IEA (2016). *World Energy Outlook 2016*, Paris: International Energy Agency.

Ito, K. and S. Zhang (2019). 'Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China', *Journal of Political Economy*, vol. **Forthcoming**.

Jayachandran, S. (2009). 'Air Quality and Early-Life Mortality Evidence from Indonesia’s Wildfires', *Journal of Human Resources*, vol. **44**(**4**), pp. 916-954.

Kerry Smith, V. and William H. Desvousges (1986). 'Averting Behavior: Does it Exist?', *Economics Letters*, vol. **20**(**3**), pp. 291-296.

Koplitz, Shannon N., Daniel J. Jacob, Melissa P. Sulprizio, Lauri Myllyvirta and Colleen Reid (2017). 'Burden of Disease from Rising Coal-Fired Power Plant Emissions in Southeast Asia', *Environmental Science & Technology*, vol. **51**(**3**), pp. 1467-1476.

Koplitz, Shannon N., Loretta J. Mickley, Miriam E. Marlier, Jonathan J. Buonocore, Patrick S. Kim, Tianjia Liu, Melissa P. Sulprizio, Ruth S. DeFries, Daniel J. Jacob, Joel Schwartz, Montira Pongsiri and Samuel S. Myers (2016). 'Public Health Impacts of the Severe Haze in Equatorial Asia in September–October 2015: Demonstration of a New Framework for Informing Fire Management Strategies to Reduce Downwind Smoke Exposure', *Environmental Research Letters*, vol. **11**(**9**), pp. 094023.

Lelieveld, J., J. S. Evans, M. Fnais, D. Giannadaki and A. Pozzer (2015). 'The Contribution of Outdoor Air Pollution Sources to Premature Mortality on a Global Scale', *Nature*, vol. **525**(**7569**), pp. 367-371.

Li, Yating, William A. Pizer and Libo Wu (2019). 'Climate Change and Residential Electricity Consumption in the Yangtze River Delta, China', *Proceedings of the National Academy of Sciences*, vol. **116**(**2**), pp. 472-477.

Liu, Haoming and Alberto Salvo (2018). 'Severe Air Pollution and Child Absences When Schools and Parents Respond', *Journal of Environmental Economics and Management*, vol. **92**, pp. 300-330.

Marlier, Miriam E., Amir S. Jina, Patrick L. Kinney and Ruth S. DeFries (2016). 'Extreme Air Pollution in Global Megacities', *Current Climate Change Reports*, vol. **2**(**1**), pp. 15-27.

Mei, T. T. (2017). 'It's hazy due to local emissions: Factories, cars behind haze in Singapore', *The Straits Times*, vol. **October 5**.

Mideksa, Torben K. and Steffen Kallbekken (2010). 'The Impact of Climate Change on the Electricity Market: A Review', *Energy Policy*, vol. **38**(**7**), pp. 3579-3585.

MOH (2017). *Air Quality Information: Health Advisory for the General Public*, Singapore: Ministry of Health and National Environment Agency, Singapore.

Molina, Mario J. and Luisa T. Molina (2004). 'Megacities and Atmospheric Pollution', *Journal of the Air & Waste Management Association*, vol. **54**(**6**), pp. 644-680.

MOM (2017). *Labour Market Statistical Information, Summary Table: Unemployment*, Singapore: Ministry of Manpower, Singapore.

MSS (2017). *Climate of Singapore*, Singapore: Meteorological Service Singapore, National Environmental Agency.

NEA (2016). *Hazy? Refer to these Guides to Plan Your Activities*, Singapore: National Environment Agency.

NEA (2017). *Revised Energy Rating System*, Singapore: National Environment Agency, Singapore.

Panasonic (2017). *CU-XS24RKZ Overview*, Singapore: Panasonic.

Quah, Euston (2002). 'Transboundary Pollution in Southeast Asia: The Indonesian Fires', *World Development*, vol. **30**(**3**), pp. 429-441.

Rapson, David (2014). 'Durable Goods and Long-run Electricity Demand: Evidence from Air Conditioner Purchase Behavior', *Journal of Environmental Economics and Management*, vol. **68**(**1**), pp. 141-160.

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*, vol. **Forthcoming**.

Sailor, D. J. and A. A. Pavlova (2003). 'Air Conditioning Market Saturation and Long-Term Response of Residential Cooling Energy Demand to Climate Change', *Energy*, vol. **28**(**9**), pp. 941-951.

Salvo, A. and D. Tan (2014). 'Multilateral Approach to Abating Regional Haze Still Apt', *The Straits Times*, vol. **June 5**.

Salvo, Alberto (2018). 'Electrical Appliances Moderate Households’ Water Demand Response to Heat', *Nature Communications*, vol. **9**(**1**), pp. 5408.

Seow, J. (2015). 'Haze forces closure of schools across Singapore: Unprecedented move due to possibility of PSI hitting hazardous levels', *The Straits Times*, vol. **September 25**.

SP (2017). *Our Businesses, SP Services, Our Services*, Singapore: Singapore Power.

SPS (2016). *Understanding the Ups and Downs of Your Utilities Bill*, Singapore: SP Services.

Sun, C., M.E. Kahn and S. Zheng (2017). 'Self-Protection Investment Exacerbates Air Pollution Exposure Inequality in Urban China', *Ecological Economics*, vol. **131**, pp. 468-474.

Tan, A. (2017). 'Industries and vehicles add to bad air days', *The Straits Times*, vol. **March 3**.

Tan, D. (2014). *A Contribution to Understanding the Impact of Transboundary Haze 2013 on Singapore*, Singapore: National University of Singapore, Undergraduate Honors Thesis.

UN (2013). *World Economic and Social Survey 2013: Sustainable Development Challenges*, New York: United Nations.

UN (2014). *World Urbanization Prospects: The 2014 Revision*, New York: United Nations.

Velasco, E. and M. Roth (2012). 'Review of Singapore's Air Quality and Greenhouse Gas Emissions: Current Situation and Opportunities', *Journal of the Air & Waste Management Association*, vol. **62**(**6**), pp. 625-641.

Watson, J. G. (2002). 'Visibility: Science and Regulation', *J Air Waste Manag Assoc*, vol. **52**(**6**), pp. 628-713.

WHO (2006). *Air Quality Guidelines for Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide: Global Update 2005*, Geneva: World Health Organization.

Wolfram, C. (2014). 'Will Smog in China Spur Climate Solutions?', *Energy at Haas*, vol. **April 21**.

Wolfram, Catherine, Orie Shelef and Paul Gertler (2012). 'How Will Energy Demand Develop in the Developing World?', *Journal of Economic Perspectives*, vol. **26**(**1**), pp. 119-138.

Yuen, Belinda and Leon Kong (2009). 'Climate Change and Urban Planning in Southeast Asia', *Surveys and Perspectives Integrating Environment & Society*, vol. **2**(**3**).

Zhang, Junjie and Quan Mu (2017). 'Air Pollution and Defensive Expenditures: Evidence from Particulate-Filtering Facemasks', *Journal of Environmental Economics and Management*.

Figures

A

Day	1	2	3	…	61	62	63	64	…	121	122	123
Household *i*	x	x	x	x	x	o	o	o	o	o	…	
Household *j*		x	x	x	x	x	o	o	o	o	o	…
Household *k*			x	x	x	x	x	o	o	o	o	o
⋮												

B **C**

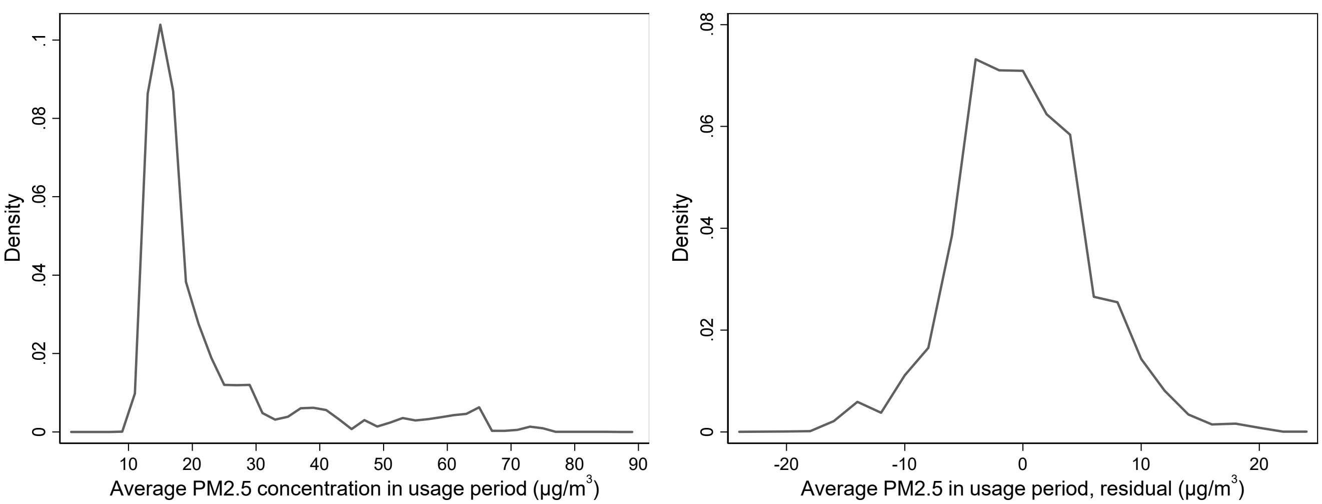

Figure 1. Empirical design: Main identifying variation is temporal. Across 130,000 households, two-month periods start on different days, according to an evenly distributed schedule of meter readings by meter-reading staff. As a result, the time series variation in the consumption-pollution data is daily variation. In the schematic shown in panel A, x = consumption in a household's first period, o = consumption in a household's second period. The difference in the first 61-day billing cycle for households *i* and *j* is day 1 minus day 62. Fig. A.1 shows the distribution of electricity and gas meter reading dates in the sample. Panel B shows the distribution of average PM2.5 over household by period observations in the electricity sample, e.g., household *i*'s first 61-day billing cycle comprises one observation (PM2.5 averaged over days marked with an x). Panel C shows the distribution of average PM2.5 over household by period observations in the electricity sample after partialing out household fixed effects (FE), share of calendar month and day type variables, year FE, electricity price interacted with dwelling type FE, and weather, i.e., all controls in the baseline regression model (Table 2 below). Across 2.1 million household by usage period observations, the range of residual pollution is -26 to 42 μg/m^3 (with panel C showing -20 to 20 μg/m^3). Fig. A.6 shows the distribution of average PM2.5 after partialing out share of month and year fixed effects only.

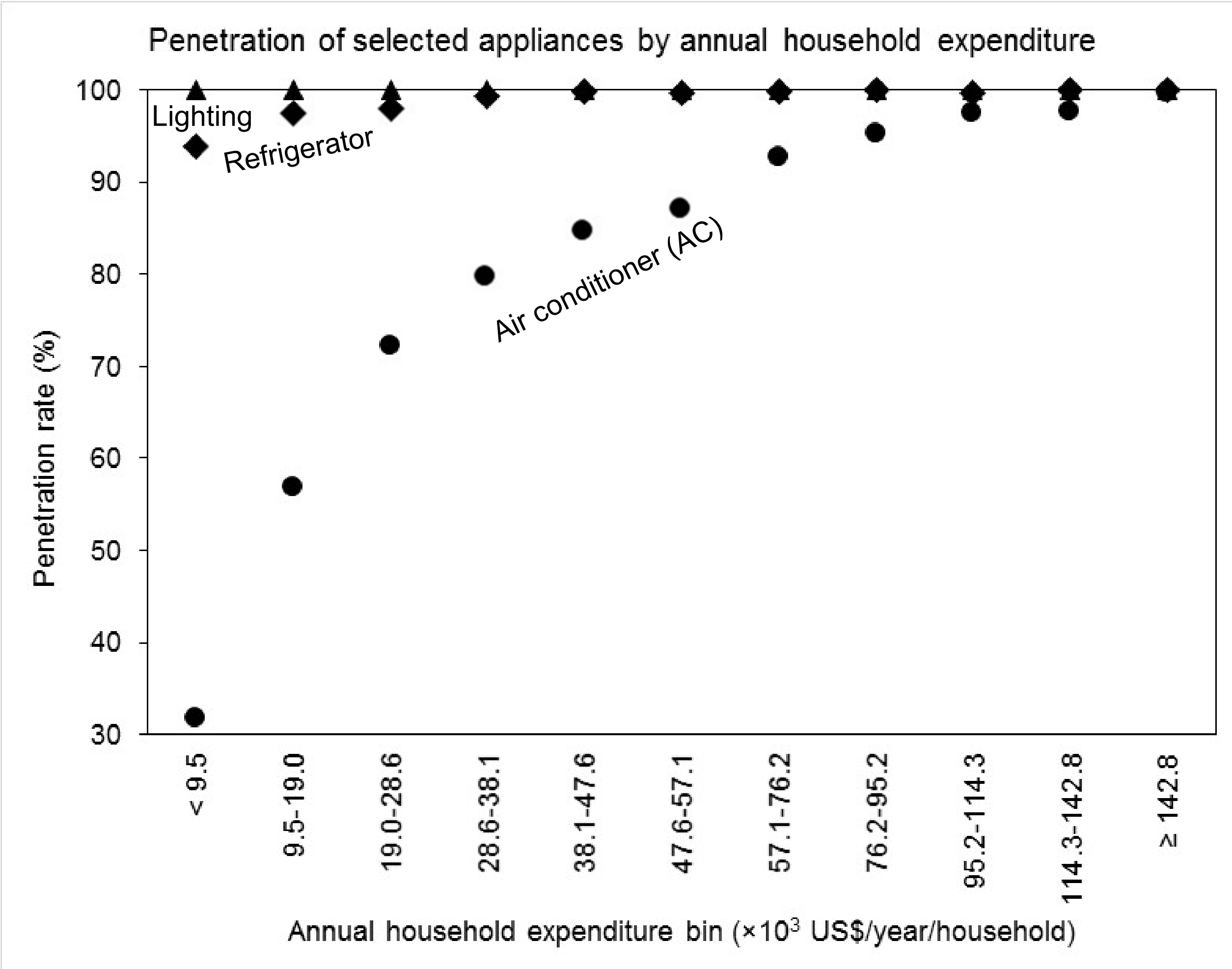

Figure 2. Household penetration rates for air conditioners (circles), refrigerators (diamonds), and lighting (triangles) by household expenditure bin in 2012/13. The unit of study is a resident household in Singapore. Annual household expenditure is expressed in thousands of US$ using an exchange rate of 1.26 SG$/US$ (nominal December 2013 prices). Source: 2012/13 Household Expenditure Survey (DOS, 2014).

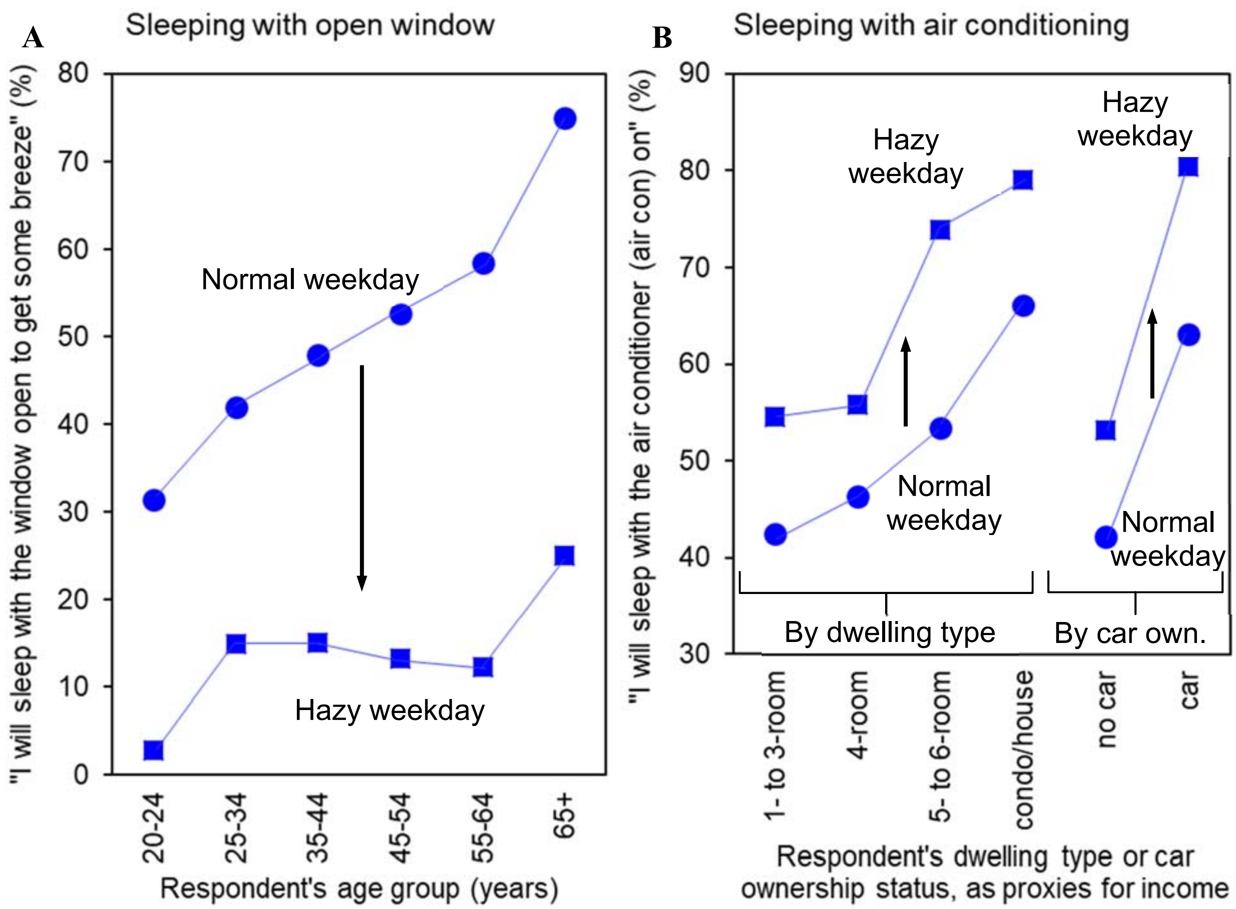

Figure 3. Haze induces sleeping with air conditioning at the expense of natural ventilation. I surveyed 311 residents of Singapore on their expected home energy behaviors on a "normal weekday," and again after asking each resident to consider "a hazy weekday." See Appendix B for details of the within-subject design. Share of respondents stating they would sleep with A, "the window open to get some breeze," by respondent's age group, and B, "the air conditioner (air con) on," by respondent's dwelling type or car ownership status, on a normal weekday vs. a hazy weekday.

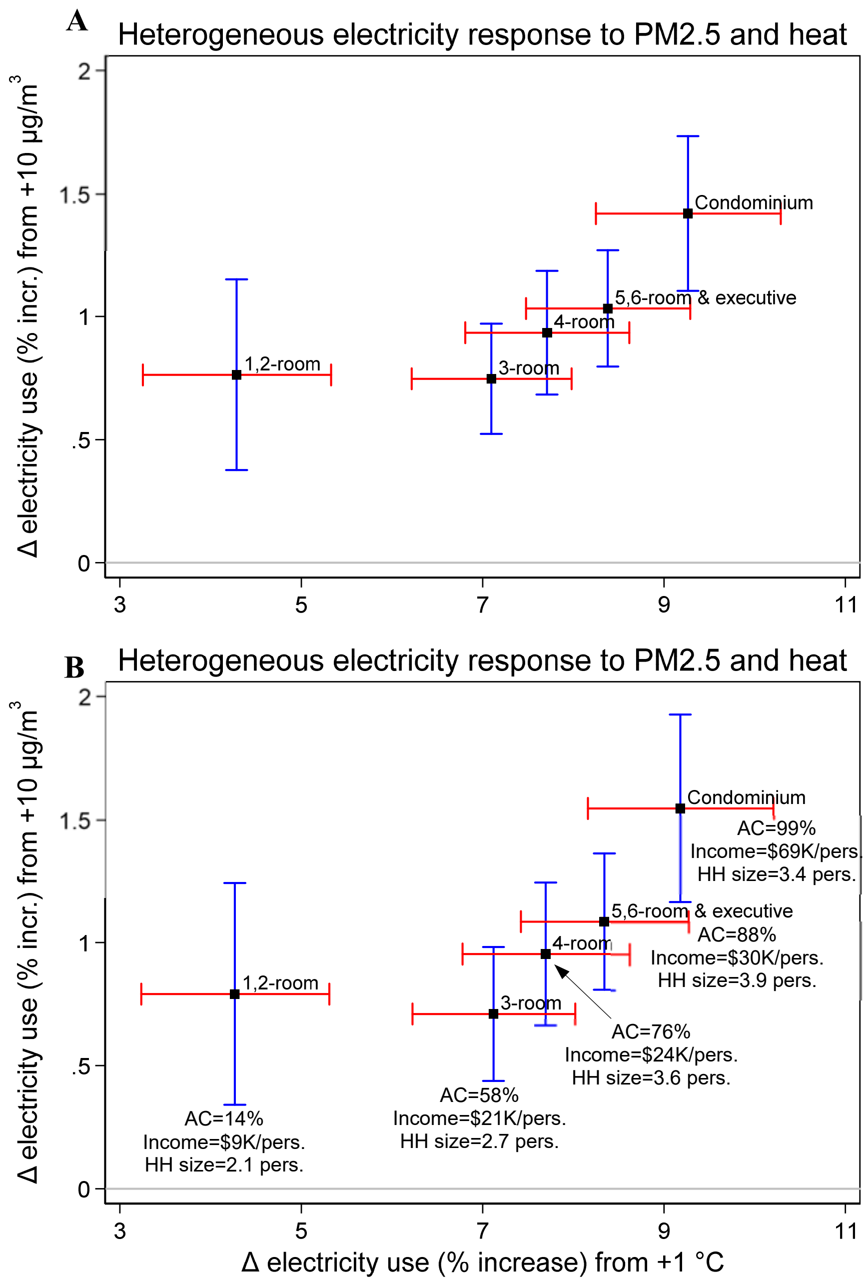

Figure 4. Heterogeneous electricity demand response to PM2.5 pollution and heat. Response to +10 μg/m^3 PM2.5 (vertical axis) against response to +1 °C temperature (horizontal axis), by apartment type. Estimates from an OLS regression in panel A, and from a 2SLS regression in panel B. Source: Variant of Table 2, columns 1-2, with (i) average temperature entering linearly (instead of in bins) to produce one summary measure; and (ii) interactions between the different apartment types and average PM2.5 (and its instruments in panel B) and average temperature. I convert the 95% CI for the apartment-type-specific PM2.5 and temperature coefficients in log points to percent changes. Also shown are AC penetration (%), mean HH income (US$/year/person), and mean HH size (persons), by apartment type, from the HES.

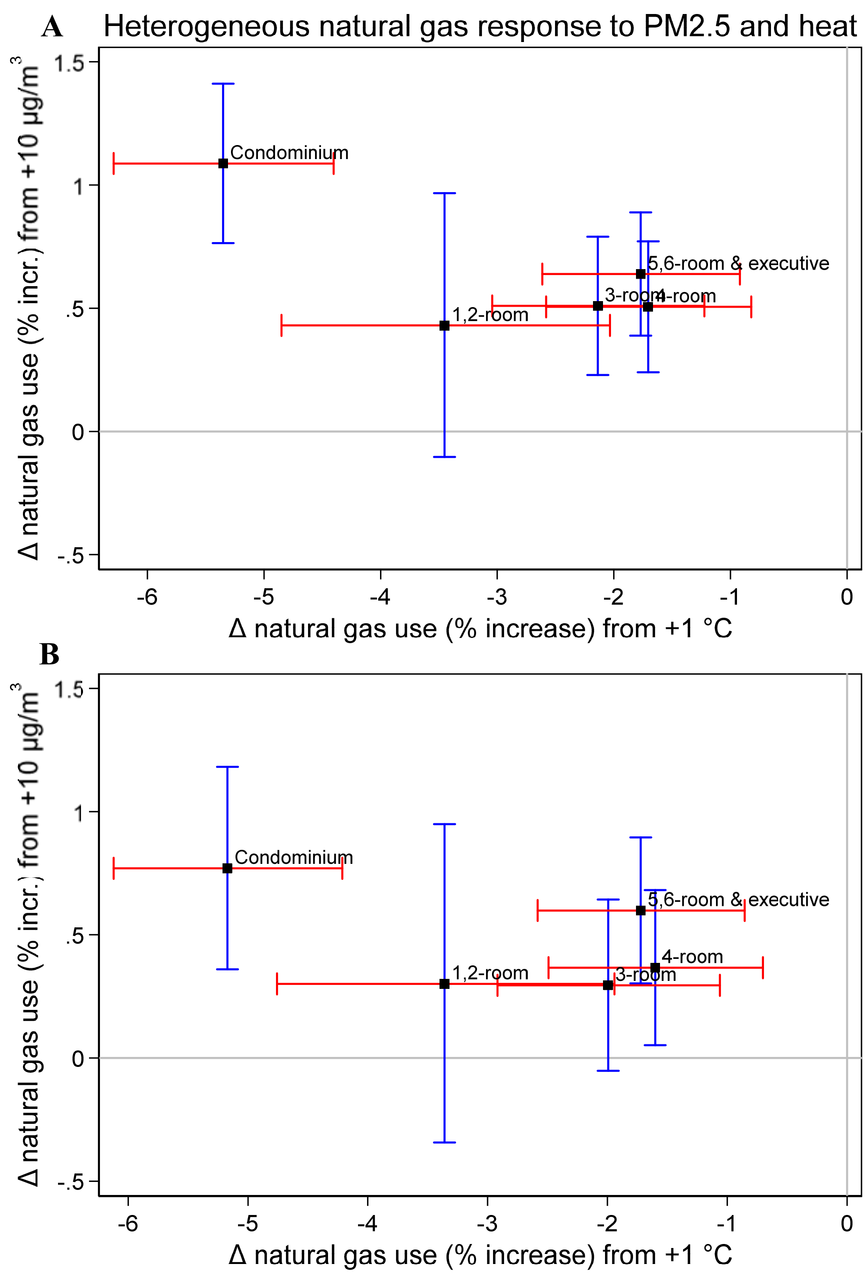

Figure. 5. Heterogeneous natural gas demand response to PM2.5 pollution and heat. Response to +10 µg/m^3 PM2.5 (vertical axis) against response to +1 °C temperature (horizontal axis), by apartment type. Estimates from an OLS regression in panel A, and from a 2SLS regression in panel B. Source: Variant of Table 2, columns 3-4, with (i) average temperature entering linearly (instead of in bins) to produce one summary measure; and (ii) interactions between the different apartment types and average PM2.5 (and its instruments in panel B) and average temperature. I convert the 95% CI for the apartment-type-specific PM2.5 and temperature coefficients in log points to percent changes.

Tables.

Table 1. Summary statistics

Variable	*N*	Mean	Std.Dev.	Min.	Max.
Electricity use (kWh/month)	2,093,683	445.91	367.28	0.98	6370.82
Natural gas use (kWh/month)	1,121,233	81.59	68.50	0	879.84
Electricity price (US$/kWh)	2,093,683	0.21	0.02	0.17	0.24
Natural gas price (US$/kWh)	1,121,233	0.17	0.01	0.15	0.19
PM2.5, East (average of daily mean, μg/m^3)	891,934	21.00	11.61	11.37	78.21
PM2.5, West (average of daily mean, μg/m^3)	397,948	22.22	13.16	9.34	88.46
PM2.5, Center (average of daily mean, μg/m^3)	167,941	19.26	10.32	8.15	66.04
PM2.5, South (average of daily mean, μg/m^3)	355,284	21.42	13.39	9.60	86.35
PM2.5, North (average of daily mean, μg/m^3)	280,576	22.24	11.08	9.65	78.84
Temperature (average of daily mean, °C)	2,093,683	27.73	0.65	26.06	29.12
Dew point depression (average at 8am, °C)	2,090,156	3.74	1.33	1.48	7.93
Share of days with some precipitation (%)	2,093,683	70.37	16.87	9.68	100
Wind speed (average of daily mean, km/h)	2,093,683	7.26	1.36	5.14	11.66
Share of public holidays (%)	2,093,683	3.18	1.59	0	12.90
Share of school holidays (%)	2,093,683	16.91	15.59	0	78.95
Spatially aggregated fire intensity in SE Asia (MW/km)	2,093,683	10.38	10.30	0.31	63.94
Share of days with thermal inversion (%)	2,090,156	28.78	22.31	0	90.32
Covariates used in robustness tests					
Relative humidity (average of daily mean, %)	2,093,683	75.39	2.52	67.66	83.54
Solar radiation (average of 7am to 6pm mean, W/m^2)	2,093,683	263.22	21.66	196.21	325.41
Industrial electricity use (average of GWh/month)	2,093,683	1607.75	55.78	1364.61	1755.43
Overall unit labor cost (avg. of real quarterly index)	2,093,683	110.28	5.79	101.03	121.51
Average wage (average of real quarterly index)	2,093,683	4770.45	305.58	4195.15	5272.27

Note. An observation is a household by usage period in the 2012-2015 microdata, trimmed at percentiles 1 and 99 of electricity or gas use by dwelling type. Only a subset of electricity-purchasing households also purchase gas from the grid. I normalize actual utility consumption by the duration of each usage observation (thus calculating kWh/month). Residential utility prices are single-block constant marginal prices (Fig. A.4). I assign area-level PM2.5 based on each household's zip code. Spatially aggregated land fire intensity in Southeast Asia is hotspot-specific radiative power weighted by the interaction of Singapore-to-hotspot inverse-distance and wind-to-bearing direction-difference. Variables are averages over the days that are concurrent to each usage observation. Source: SP Services microdata, Energy Market Authority, City Gas Pte Ltd, National Environment Agency, Meteorological Service Singapore, NASA FIRMS, NOAA IGRA2, Singapore Department of Statistics, NUS Geography weather station (relative humidity, solar radiation).

Table 2. Air pollution raises home energy use

Dependent variable is:	Log electricity use		Log natural gas use		Log electricity use, among HHs that concurrently purchase natural gas			
	(1) OLS coeff. (se)	(2) 2SLS coeff. (se)	(3) OLS coeff. (se)	(4) 2SLS coeff. (se)	(5) OLS coeff. (se)	(6) 2SLS coeff. (se)	(7) OLS coeff. (se)	(8) 2SLS coeff. (se)
PM2.5 (per 10 μg/m^3, mean over usage period of daily means)	0.0104*** (0.0012)	0.0112*** (0.0013)	0.0089*** (0.0012)	0.0085*** (0.0013)	0.0117*** (0.0012)	0.0128*** (0.0013)	0.0102*** (0.0011)	0.0114*** (0.0012)
Temperature ∈ [26.9,27.3) °C (mean over usage period of daily means)	0.0214*** (0.0053)	0.0215*** (0.0053)	-0.0038 (0.0064)	-0.0039 (0.0064)	0.0292*** (0.0050)	0.0294*** (0.0051)	0.0298*** (0.0046)	0.0300*** (0.0046)
Temperature ∈ [27.3,27.7) °C	0.0299*** (0.0075)	0.0300*** (0.0075)	-0.0287*** (0.0083)	-0.0288*** (0.0083)	0.0407*** (0.0068)	0.0407*** (0.0069)	0.0449*** (0.0062)	0.0449*** (0.0062)
Temperature ∈ [27.7,28.1) °C	0.0523*** (0.0098)	0.0518*** (0.0098)	-0.0409*** (0.0106)	-0.0407*** (0.0106)	0.0631*** (0.0091)	0.0624*** (0.0091)	0.0691*** (0.0081)	0.0683*** (0.0081)
Temperature ∈ [28.1,28.5) °C	0.0728*** (0.0097)	0.0718*** (0.0097)	-0.0602*** (0.0106)	-0.0597*** (0.0106)	0.0880*** (0.0091)	0.0866*** (0.0091)	0.0966*** (0.0082)	0.0949*** (0.0082)
Temperature ≥ 28.5 °C	0.0872*** (0.0098)	0.0863*** (0.0098)	-0.0641*** (0.0111)	-0.0638*** (0.0111)	0.1049*** (0.0096)	0.1038*** (0.0096)	0.1141*** (0.0086)	0.1127*** (0.0086)
Log natural gas use (over usage period)							0.1476*** (0.0014)	0.1476*** (0.0014)
Number of observations	2,089,190	2,089,190	1,113,476	1,113,476	1,111,111	1,111,111	1,100,855	1,100,855
Number of regressors (less HH FE)	38	38	38	38	38	38	39	39
Number of HHs	126,233	126,233	70,144	70,144	69,715	69,715	69627	69627
First-stage F-statistic (2 excl. instr.)		1,566		1,518		1,320		1,317

Note. The table reports estimates for 8 electricity or gas use regressions. An observation is a household (HH) by usage period in the 2012-2015 microdata, trimmed at percentiles 1 and 99 of electricity or gas use by dwelling type. The dependent variable is log electricity or gas use. Columns 5 to 8 restrict the sample to electricity-purchasing HHs that also purchase gas from the grid. All covariates are averages over the days that are concurrent to each usage observation. The empirical support for average PM2.5 is 8-88 μg/m^3. Granular temperature control, with reference category for average < 26.9 °C. Other controls are average dew point depression and wind speed, the share of days with some precipitation, share of month and day type variables, utility price interacted with dwelling type fixed effects (FE), year FE, and HH FE. Odd-numbered columns report OLS estimates. Even-numbered columns report 2SLS estimates, where pollution is instrumented with average regional land fire intensity and incidence of thermal inversion in Singapore. Standard errors (se) two-way clustered by HH and last day of bill. ***Significant at 1%, **at 5%, *at 10%.

Table 3. Electricity demand responds more to pollution in local markets with higher incomes; other environmental controls

The dependent variable is log electricity use.	**One temperature control (not bins)**		**PM2.5 and heat interacted with income**		**Include $PM \times T$**	**Omit PM**	**Omit PM & other W**	**Prop. "bad air" days**
	(1) OLS coeff (se)	**(2) 2SLS coeff (se)**	**(3) OLS coeff (se)**	**(4) 2SLS coeff (se)**	**(5) 2SLS coeff (se)**	**(6) OLS coeff (se)**	**(7) OLS coeff (se)**	**(8) OLS coeff (se)**
PM2.5 (per 10 μg/m^3, mean over usage period of daily means)	0.0104*** (0.0011)	0.0107*** (0.0012)	0.0080*** (0.0013)	0.0075*** (0.0015)	0.6001*** (0.1465)			
PM2.5 × market-level proportion of high-income HHs			0.0053*** (0.0018)	0.0069*** (0.0021)				
Temperature (°C, mean over usage period of daily means)	0.0725*** (0.0054)	0.0722*** (0.0053)	0.0572*** (0.0056)	0.0575*** (0.0057)	0.1048*** (0.0106)	0.0822*** (0.0054)	0.0978*** (0.0043)	0.0727*** (0.0053)
Temperature × market-level proportion of high-income HHs			0.0322*** (0.0035)	0.0311*** (0.0035)				
Interaction: PM2.5 × temperature (10 μg/m^3 × 1 °C)					-0.0207*** (0.0051)			
Daily mean PM2.5 $\in [40,50)$ μg/m^3 (prop. of days in period)								0.0718** (0.0337)
Daily mean PM2.5 $\geq$ 50 μg/m^3 (proportion of days in period)								0.0982*** (0.0137)
Number of observations	2,089,190	2,089,190	1,981,389	1,981,389	2,089,190	2,089,190	2,092,717	2,089,190
Number of regressors (less HH FE)	34	34	36	36	35	33	30	35
Number of HHs	126,233	126,233	118,984	118,984	126,233	126,233	126,233	126,233

Note. The table reports estimates for 8 OLS or 2SLS regressions of log electricity use. An observation is a household (HH) by usage period. The regressors of interest are average daily mean PM2.5 (per 10 μg/m^3) and temperature (°C) and, in columns 3-4, their separate interaction with the HITS income measure for the HH's zip code and dwelling type. This local-market income measure is the proportion of households with high-earning members and has empirical support 0-1. Instead of average PM2.5, column 8 specifies the proportion of days with daily mean PM2.5 in different elevated ranges. As in Table 2, all regressions control for share of month and day type, electricity price interacted with dwelling type FE, year FE, HH FE (which subsume HITS income in columns 3-4), and, except for column 7, weather. 2SLS instruments for pollution (and, in columns 4 and 5, its interaction with income or temperature) with regional land fire intensity and thermal inversion in Singapore (and, in columns 4 and 5, interactions between these instruments and income or temperature). Standard errors (se) two-way clustered by HH and last day of bill. ***Significant at 1%, **at 5%, *at 10%.

Table 4. Household electricity demand under counterfactual PM2.5 pollution and heat in 2014

	All dwelling types: AC penetration = 76%						Condominium apartments: AC penetration = 99%		
	Singapore Actual:	Change: Counterfactual − Actual					Singapore Actual:	Change: Counterfactual − Actual	
	kWh / month / household	kWh / month / household(1)	GWh / year(2)	US$ / year / household(3)	million US$ / year(2),(3)	thousand tons CO_2 / year(2),(4)	kWh / month / household	kWh / month / household	US$ / year / household
P1 Singapore exposed to PM2.5 recorded in Beijing	445	+31 [+27,+35]	+486 [+421,+551]	+82 [+71,+93]	+107 [+93,+121]	+219 [+189,+248]	602	+60 [+46,+74]	+157 [+121,+194]
P2 Singapore exposed to PM2.5 recorded in Kolkata	445	+24 [+19,+28]	+368 [+303,+434]	+62 [+51,+74]	+81 [+67,+96]	+166 [+136,+195]	602	+48 [+34,+62]	+126 [+89,+163]
P3 Singapore exposed to PM2.5 recorded in Dhaka	445	+23 [+19,+27]	+360 [+302,+417]	+61 [+51,+71]	+79 [+67,+92]	+162 [+136,+188]	602	+45 [+33,+57]	+119 [+87,+151]
T Singapore exposed to +1 °C heat	445	+32 [+30,+33]	+496 [+473,+518]	+84 [+80,+88]	+109 [+104,+114]	+223 [+213,+233]	602	+42 [+37,+48]	+112 [+98,+126]

Note. Counterfactual scenarios P1-P3, Raising PM2.5 in Singapore to levels recorded over the annual cycle in Beijing (2014 mean = 98 μg/m^3), Kolkata (the first year available, 2016 mean =84 μg/m^3), and Dhaka (the first year available, 2017 mean = 80 μg/m^3)—see Figs. B.2 and B.3. Counterfactual scenario T, Raising mean daily temperatures by 1 °C. The predicted demand response considers behavior along the intensive margin using the pooled sample (76% AC penetration in 2012/13) or the AC-saturated condominium apartment subsample, per Fig. B.1, panel B estimates. Changes to AC penetration from the counterfactual environmental degradation are not considered. Point estimates and 95% CI in square brackets. Superscript (1): Considers all household by usage period pairs observed between actual meter readings closing in January to December 2014. Superscript (2): Considers 1.3 million households. Superscript (3): Considers the residential electricity price in June 2014 (Fig. A.4). Superscript (4): Considers Singapore's CO_2 emission factor in 2013 (the electricity fuel mix is predominantly natural gas).