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Analysis

Improving stove evaluation using survey data: Who received which intervention matters

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ABSTRACT

As biomass fuel use in developing countries causes substantial harm to health and the environment, efficient stoves are candidates for subsidies to reduce emissions. In evaluating improved stoves' relative benefits, little attention has been given to who received which stove intervention due to choices that are made by agencies and households. Using Chinese household data, we find that the owners of more efficient stoves (i.e., clean-fuel and improved-biomass stoves, as compared with traditional-biomass and coal stoves) live in less healthy counties and differ, across and within counties, in terms of household characteristics such as various assets. On net, that caused efficient stoves to look worse for health than they actually are. We control for counties and household characteristics in testing stove impacts. Unlike tests that lack controls, our preferred tests with controls suggest health benefits from clean-fuel versus traditional-biomass stoves. Also, they eliminate surprising estimates of health benefits from coal, found without using controls. Our results show the value, for learning, of tracking who gets which intervention.

1. Introduction

Approximately 3 billion people in developing countries face health risks associated with the use of biomass for energy such as the burning of wood, dung and crop residues (IEA, 2010).[2] Exposures largely are indoors, given higher indoor concentrations and all the time spent indoors (Smith et al., 2004). Biomass fuels often are used in poorly ventilated places, with open fires or inefficient stoves, yielding pollutant levels well above the average exposures within a dirty city (Smith, 1993). These exposures often vary greatly by household member (Smith et al., 2004), as men spend more time outdoors while children spend time indoors with women, who are cooking.

The World Health Organization found that indoor smoke accounts for almost 4% of the burden of disease in developing countries, ranking indoor air pollution 4th among all the sources of disease burden — following malnutrition, unprotected sexual relations, and poor water quality and sanitation (Ezzati et al., 2004). That magnitude motivates, at the least, quality evaluation of interventions.

Those facts have led to studies of health risks and biomass fuel use. Published evidence suggests that changes in what biomass is used, and how, can reduce related risks to health (Boy et al., 2002; Bruce et al., 1998, 2004; IARC, 2010; McCracken et al., 2007; Mishra et al., 2004).[3] Major reviews have concluded that household air pollution from solid cookfuels is associated with risks of chronic obstructive pulmonary disease (COPD), lung cancer, cardiovascular disease, cataracts, and child acute lower respiratory infections (ALRI) (Lim et al., 2012). Evidence is growing of other important outcomes including tuberculosis, cervical cancer, adverse pregnancy outcomes, asthma, and cognitive effects in children (Baumgartner et al., 2011; Dix-Cooper et al., 2012; Lin et al., 2007; Pokhrel et al., 2010; Pope et al., 2010; Velema et al., 2002; Wong et al., 2013). Such findings have inspired projects worldwide, e.g. the Global Alliance for Clean Cookstoves, to disseminate and to commercialize emissions-reducing stoves.

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[1] Co-lead authors.
[2] We focus on direct local health impacts but note that indoor pollution becomes outdoor and atmospheric pollution. IPCC's 4th Assessment Report says household usage of biomass and coal for energy contributes to carbon emissions.
[3] Recommended action may differ for developed countries. Moshammer et al. (2006) suggest room ventilation, e.g., following analysis of the impact on children's lung function of cooking with natural gas (a 'clean' fuel in our work).

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Many findings on impacts of stove interventions are however subject to selection biases given various choices by agencies and households (Heckman and Smith, 1995) — which can lead the stove that a person uses to be correlated with her health for reasons other than stove impacts. Such correlations can confound the accurate estimation of an improved stove's impact on health. For example, clean stoves might be adopted more by those with poor housing ventilation, as their benefits from lowering stove emissions may be higher given longer exposure to those emissions. If that is so and in addition poor ventilation is associated with a low score on the health measures used in an evaluation,[4] it is easy for that evaluation to underestimate the clean stove's benefit.[5]

To illustrate how such confounding correlations might come about, due to local choices, we provide background about stoves in China.[6] We then describe our household data from China and analyze it using regression and matching techniques[7] (Abadie and Imbens, 2002; Rosenbaum and Rubin, 1983) to address confounding influences. We see that biased impact estimates arise from non-random distributions of improved stoves. Different stoves (coal, traditional-biomass, improved-biomass, and the 'clean-fuel' which use electricity, liquefied petroleum gas, or biogas) are owned by households who differ in health-relevant characteristics, e.g., some are older or are poorer or have kitchens featuring poorer ventilation. Such differences, if correlated with stoves, create the potential for biases in stove-impact evaluations, if they are not adequately addressed.

Given our dual goal of both highlighting and, at least in part, addressing potential biases, we present our different results in two ways. We provide the impact estimates from our preferred specifications, which all include individual and household characteristics plus county indicators. For example, versus traditional-biomass stoves, we find gains from using clean-fuel but not from improved-biomass stoves. We find no benefits from clean-fuel versus improved-biomass stoves, nor gains from any other stoves relative to coal stoves. The latter is surprising, given past results.

We also show how the inclusion of counties and of household characteristics significantly shifted our estimates. Without including controls, our analyses comparing to traditional-biomass suggest no benefit from the clean-fuel and, if anything, losses from the improved-biomass stoves. The reason is that the owners of more efficient stoves (clean-fuel, improved-biomass) are poorer and live in counties where, on average, people are less healthy. Controls for such key differences suggest gains from more efficient stoves. We also find that the traditional-biomass stoves appear to be *worse* for health than coal, controlling only for the provinces, but this result vanishes if we include indicators for county, i.e., finer controls for differences in local policies and conditions. Even when controlling for county, though, the improved-biomass stoves appear *worse* for health than coal stoves. Inclusion of household characteristics eliminates that surprising result. In sum, intuitive effects are supported and counterintuitive ones eliminated by including more controls.

The rest of the paper is as follows. Section 2 describes relevant stove programs in China. Section 3 presents the large data set at our disposal, based upon a survey of Chinese households. Section 4 presents our methods and sketches why household decisions can complicate evaluation in a simple regression framework. Section 5 then provides our results, while Section 6 concludes.

2. Stove Programs & Stove Adoption

From the early 1980s, the Chinese National Improved Stove Program (NISP) facilitated the dissemination of efficient biomass and improved coal stoves (Sinton et al., 2004), in support of 860 counties (of 2126 countrywide). Some provinces and counties took separate initiatives to promote stoves. The Agriculture Ministry was responsible for direct subsidies to households, who paid for materials and installation. The fraction of their costs that was subsidized depended on the stove and the county. Counties applied for such funding and were chosen to participate based on, e.g., energy shortages and their willingness to share the cost. The partial subsidies, until 1990, led to rapid stove dissemination (Smith et al., 1993). Although primarily designed to improve fuel efficiency, NISP only disseminated chimney stoves, which also lowered indoor pollution levels (Edwards et al., 2007).

During the 1990s, though, stove distribution no longer relied on subsidies to households (rural energy companies still received tax and loan benefits, plus training and administrative support (Sinton et al., 2004). The Ministry of Health, however, had a separate program to reduce fluorosis in areas dependent on high-fluoride coal. A State Development Planning Commission supported stoves to promote reforestation and reduce floods (Sinton et al., 2004). To reduce biomass usage — a goal unrelated to health — the latter agency promoted rural coal markets to convert biomass users to use of coal.[8]

Over time, household choices became more important to the distribution of these stoves, particularly given a phasing out of subsidies after 1990. Sinton et al. (2004) state: "Unlike many improved stove programs in other countries (such as India), households bore most of the direct costs of stove purchases." (p.39); and, further: "Households paid about 94% of all costs" (p. 40). Which households received which if any of the new stoves being promoted, then, very likely was driven by factors determining related household choices, including liquidity or credit constraints, preferences, and knowledge about such stoves. Household choices clearly can be critical, while the details of what programs were promoted and where obviously also affect stove allocations.

3. Data

We use a cross-sectional survey of about 3500 households within three provinces in China (Shaanxi, Hubei, and Zhejiang) that was collected in 2001–2003 to help evaluate policy impacts. It includes information on: health outcomes for adults (age 18 and over); demographics; fuel use; and the use of stoves by type (Sinton et al., 2004). We focus on stoves used mainly for cooking. Four types are in our sample: traditional-biomass (16%), improved-biomass (47%), coal (32%), and clean-fuel (6%). Stoves are defined by the types of fuels they use. Both traditional-biomass and improved-biomass stoves

[4] Bruce et al. (1998) and Dasgupta et al. (2006), for instance, demonstrate that related dwelling characteristics are, in fact, significant determinants of the health outcomes within studies done in Guatemala and Bangladesh, respectively.

[5] A bias in the opposite direction is also possible. See the discussion within Section 2 below, and in Pitt et al. (2006), where the story is not higher marginal damages without ventilation but lower earning losses if the sick are exposed.

[6] Peabody et al. (2005) compare effects of using traditional biomass, improved biomass, or clean cooking stoves relative to coal on a suite of health outcomes. They find significant benefits of improved biomass stoves in reducing respiratory disease, COPD and exhaled carbon monoxide (CO), and in increasing forced vital capacity (FVC) or lung capacity. Improved biomass stoves also do better than traditional biomass stoves for respiratory disease, COPD, exhaled CO, and FVC. History of asthma was not found to be a significant determinant in either comparison. We use self-reported health to consider additional comparisons of stove types using the China household survey analyzed in some other work (Edwards et al., 2007; Peabody et al., 2005; Zhang and Smith, 2007).

[7] Matching has been used to estimate impacts for job training (Dehejia and Wahba, 1999; Heckman et al., 1997), health (Hill et al., 2003) and forest conservation (Andam et al., 2008; Pfaff et al., 2009; Robalino and Pfaff, 2013). Applications to stoves are scarce (Mueller et al., 2011). Some have randomized stoves (Bensch and Peters, 2012; Hanna et al., 2012; Mobarak et al., 2011; Smith et al., 2006). That addresses many of the behaviorally based potential biases (without demonstrating their magnitudes).

[8] This can affect stoves' associations with health: if wealthier households in target regions are healthier than others, if coal stoves are promoted, and if the wealthier adopt them more, then non-health policy links coal to better health.

use wood, crop residues or dung. An improved-biomass stove also features at least a flue and a grate. Coal stoves use coal, coke or lignite. The clean-fuel category includes electric, liquefied petroleum gas and biogas stoves. Ranking by associations with health: coal is worst; traditional-biomass; improved-biomass; and then clean-fuel (Peabody et al., 2005).

We focus on a self-reported measure of health status, based on a set of 12 questions about physical and mental distress which is referred to as the "SF-12" (Ware et al., 1995). We focus on physical distress, not mental, by computing a Physical Component Summary (PCS) from all of the answers to the SF-12. This summary index is standardized to run from 1 to 100.[9] Scores over 50 are above average; under 50 means below average. The standard deviation is 10; that facilitates interpretation, since each point is equivalent to one-tenth of a standard deviation. A significant advantage of this measure is that the 12 questions are easy to include in a standard household survey, without additional measurement techniques beyond talking with participants. A drawback is that it is based upon self-reports, which may be subject to measurement error.[10]

We follow the public-health literature concerning which covariates affect health. Dasgupta et al. (2006) find that home ventilation affects exposure. It is affected by wall and roof materials, openings in the kitchen, as well as the possession of an open-air or a detached kitchen. Ezzati et al. (2000) and Ezzati and Kammen (2001a,b) find that the time spent nearby to cooking changes exposure.[11] Age, gender, wealth and smoking are often included. We include indicators for age ranges (26–40, 41–55, >55), whether one is male, is a smoker, is in a household that earns over 12,000 Yuan annually,[12] and has a separate open-air kitchen, a washing machine or a television. We control for the number of kitchen openings (1, 2, >2) and the minutes spent cooking in a day. Some of our specifications substitute dummy variables for the few continuous measures we have (age, income, number of kitchen openings). In continuous specifications, we add quadratic terms.

Table 1 presents ordinary least squares (OLS) results for the PCS — excluding stove types. Many explanatory factors have the anticipated effects on the PCS, though goodness-of-fit is low. Greater age worsens health. Greater wealth (income and assets) is associated with better health, e.g., television ownership raises the PCS by a quarter of a standard deviation. Across significant coefficients, kitchen openings are linked with higher PCS. The significance of such factors holds (see Appendix Table A.1) when using this specification for forced expiratory volume 1 (FEV1), an oft-analyzed objective measure of lung capacity, as an alternative health dependent variable.

Table 1 shows not only that individual and household differences are relevant for health but also that, controlling for them, unobserved differences across counties are relevant as well. Looking ahead to motivate various specifications below that aim to address selection biases, it must be that the groups using different stoves differ along some of the dimensions in Table 1.

Table 1
Determinants of the Physical Component Summary (excluding stove indicators).

	(1)		(2)	
	OLS coefficients	Std. errors	OLS coefficients	Std. errors
Age 26–40	−1.57***	0.56		
Age 41–55	−4.20***	0.59		
Age > 55	−8.74***	0.64		
Age			−0.05	0.06
Age squared			0.00***	0.00
Male	1.03**	0.42	1.28***	0.42
Income > 12,000 Yuan	0.48	0.36		
Income (1000 s Yuan)			0.04**	0.02
Income squared			−0.00	0.00
Own washing machine	0.76**	0.36	0.63*	0.36
Own tv	2.46***	0.52	2.03***	0.53
Cooking time (minutes/day)	−0.00†	0.00	−0.01	0.01
Cooking time squared			0.00	0.00
Smoker	0.62	0.47	0.55	0.46
One kitchen openings	−2.18***	0.72	−2.17***	0.71
Two kitchen openings	−1.94***	0.72	−1.88***	0.72
More than two kitchen openings	−1.38*	0.75	−1.26*	0.74
Additional open air kitchen	0.39	0.56	0.49	0.70
Heyang	1.09	0.74	1.15	0.74
Lintong	−1.68**	0.66	−1.53**	0.66
Yanchuan	0.18	0.94	0.25	0.93
Hancheng	1.22	0.79	1.34*	0.79
Suizhou	−3.07***	0.72	−3.12***	0.72
Changyang	−2.19***	0.73	−2.15***	0.73
Tongcheng	−2.46***	0.90	−2.48***	0.89
Xiantao	−1.17*	0.71	−1.17*	0.70
Yicheng	−2.23***	0.67	−2.16***	0.67
Anji	1.23*	0.74	1.48**	0.74
Kaihua	1.50*	0.82	1.62*	0.82
Xianju	0.17	0.81	0.34	0.81
Chunan	0.20	0.75	0.39	0.75
Tongxiang	0.86	0.73	0.95	0.74
Constant	51.93***	1.18	54.40***	1.77
Adjusted R − squared	0.13		0.15	
Root MSE	7.96		7.90	
Observations	3587		3587	

Omitted categories: age 18–25; enclosed kitchen; Fuping.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.
† $p < 0.11$.

4. Methodology

We illustrate here some potential challenges for statistical analysis to infer stove impact and link those challenges to empirical efforts we make to improve evaluations of such impacts.

4.1. Regression Analysis of Stove Impacts

We study stove impacts by estimating a health production function $h(s, t, m, \theta)$ including expenditures of funds (s) and time (t) to reduce exposures, plus medical expenditures (m) and the individuals' characteristics (θ).[13] We explain individual health outcomes (h_{ij} for person i county j) using their stove types (s_{ij}) plus their characteristics (θ_{ij}), including wealth, using regression (1). Lacking data on time and medical cost, those go into the error. We include dummy variables for county (C_j) to control for

[9] Ware et al. (1995) provide SAS code for computing this index. These scores are standardized according to the U.S. population mean and standard deviation. Studies validating the SF-12 survey for the Chinese case are absent, however, there are studies that justify the SF-36 version (Lam et al., 1998, 2005).

[10] Recent findings have shown that measures of general self-reported health status are, in fact, correlated with a suite of documented physical illnesses (see, for instance, Butrick et al., 2008; DeSalvo et al., 2009; Peabody et al., 2006).

[11] We thank a reviewer both for emphasizing that total cooking time is highly unequally shared by members of the typical developing country household and for noting that more efficient stoves may reduce that total cooking time. The latter correlation could help to explain why cooking time is not significant within Table 1, which lacks stoves.

[12] This income level is roughly 1449 US dollars using the exchange rate in 2002 following Peabody et al. (2005).

[13] For a review of conceptual models that depict how household decision-making affects environmental and health outcomes in developing countries, see Pattanayak and Pfaff (2009).

unobserved characteristics, such as local governance or energy supply:

$$h_{ij} = \alpha + s_{ij}\beta + \theta_{ij}\delta + C_j\gamma + \left(\varepsilon_{ij} + t_{ij}\mu + m_{ij}\sigma\right). \quad (1)$$

We study stove-type pairs, as multiple stove impacts are hard to identify at once. Versions of (1) are common in the stove-evaluation literature; sometimes data are found for t or m, which helps. Critically, though, factors θ_{ij} and C_j are not always included. Our motivation for their inclusion is clear once one considers agency and household choices. Counties not eligible for stove subsidies, or with limited access to an improved stove, effectively face higher prices — and may adopt less. In a county with access, individuals with poor health or related conditions (age, poor ventilation) may perceive higher stove benefits. Those with higher income may perceive stove costs as lower. Stove programs' details, plus household choices, make s_{ij} a function of characteristics C_j and θ_{ij}:

$$s_{ij} = k + \theta_{ij}\tau + C_j\varsigma + \eta_{ij}. \quad (2)$$

That θ_{ij} and C_j are both in Eq. (2), determining which stoves individuals possess, and in Eq. (1), determining health outcomes independent of stove use, implies a potential for biases within Eq. (1) where we are attempting to estimate impacts of the stoves s_{ij} on health h_{ij}.[14] That is our rationale for including all the Table 1 covariates in (1) — using both regression and matching approaches.[15]

For example, poverty (in income or wealth) may increase vulnerability to any exposures, lowering health conditional upon exposures. Poverty may also lower one's ability to buy a stove. Richer, healthy households may adopt new stoves more often, making new stoves look healthier even if the 'improved' stoves on offer are coal stoves promoted to save trees and lower flooding.

4.2. Matching Analysis of Stove Impacts

Several methods can be used to address potential bias from the non-random distributions of interventions, such as when the allocation of a stove is a function of θ_{ij} and C_j, as in (2) above (Angrist and Krueger, 1999). Matching techniques can be helpful in first documenting and then taking into account the non-randomness along various observed dimensions, as discussed above (see Morgan and Harding, 2006 for a review). We apply covariate matching (Abadie et al., 2004) as well as propensity-score matching (Rosenbaum and Rubin, 1983) approaches to help estimate health impacts associated with improved stoves, using comparisons of multiple stove-type pairs.

The point of matching is to compare the "treated" households receiving improved stoves with *otherwise similar households* who did not receive an improved stove. Their "similarity" is defined using non-stove determinants of health from (1) that also affect stoves possession in (2). We attempt to do "apples to apples" comparisons of people with improved stoves versus without, focusing on their similarity defined by C_j and θ_{ij}, i.e., county, household and individual observed characteristics that are in both (1) and (2). Covariate matching uses the Euclidean distance in the space (C_j, θ_{ij}) to define similarity, comparing individuals with the improved stove in question to the owners of a comparison stove who are the least far away in that space (Abadie et al., 2004).[16] Propensity-score matching matches individuals based on the values of their 'propensity scores' or predicted likelihoods of having an improved stove (propensities), from Probits using θ_{ij} and C_j.[17]

We compare outcomes for every stove pairing[18]: [1] Clean Fuel vs. Traditional Biomass; [2] Improved Biomass vs. Traditional Biomass; [3] Clean Fuel vs. Improved Biomass; [4] Clean Fuel vs. Coal; [5] Improved Biomass vs. Coal; and finally also [6] Traditional Biomass vs. Coal. In using matching to search the untreated for individuals similar to those with improved stoves, higher quality matches are found if the untreated set is larger. Thus, for each stoves pair, we use the smaller set as 'treated' and reverse the sign when needed to estimate improved-stove impacts. This means that for comparisons [1,3,4,6] above, we estimate an 'average treatment effect on the treated' (ATT), while for [2,5], we estimate an 'average treatment effect on the controls' (ATC). ATC and ATT are the same when the impact of a stove on health is invariant to characteristics, e.g., shifting from one stove to another helps a rich household as much as it does a poorer one.

Given counties' effects in Table 1, for some matching specifications we compare within the same county. However, that limits the set of untreated points, lowering the matching quality. Thus, in this case we use only the single most similar untreated point and we restrict ourselves to the counties with non-trivial fractions for each of the types within the stoves pair (if a county has 99% coal stoves, we cannot legitimately claim to empirically compare two stoves in that county). The option to try such improved comparisons emphasizes the value of our large initial data set.

We include cooking time as a covariate in the matching to better isolate the effect of the reduction in stove emissions per unit of cooking time — often a central focus of new stove design. Improved stoves also may systematically shift the time cooking per meal.[19] If that were the case, then our default analyses might be missing an additional effect. Thus, we also provide estimates from specifications that exclude cooking time from the covariates used in matching individuals.

5. Results

We start by examining the facts of stove ownership to see who possesses the stove types. Having identified some key dimensions along which the groups who own different stoves differ, next we present regression analyses in which we increase, in steps, the set of controls we include. Finally, we provide matching analyses — a form of shifting the way in which we employ controls.

5.1. Stove Types' Distributions

5.1.1. Stove & County Facts

Table 2a presents stove variations across counties. The different stoves are not being used in equal portions across counties. Coal-stove

[14] Bias also can result from a correlation of ε_i and η_i, a potential bias that is not addressed in Eq. (1) nor by matching on observables. That is one core motivation for the use of randomization, if possible, for learning from an intervention.

[15] If there existed a variable z strongly correlated with stove use in Eq. (2) but without any direct effect on health in Eq. (1), then we could use it as an instrument for s^q_{ij} in order to estimate β in Eq. (1). Such z could be random stove assignment.

[16] We use Stata's *nnmatch* for covariate matching (Abadie et al., 2004). We specify that 1 (or 2) controls be matched to each treated observation. This allows for ties: if multiple control observations have the same (lowest) distance, all are used. Thus, some treated observations are compared to more than the 1 (or 2) control observations we specified.

[17] We always sample controls with replacement. Any control observation could be matched to more than one treated.

[18] We focus on the impact of the primary cooking stove, ignoring other stoves that, in our sample, often are used for heating water or the home. Ideally, we would separate out impacts by stove but we have too few observations to do matching on each controlling for others. Thus, when doing bias adjustment after matching we use a dummy variable for whether the household uses multiple stoves, as a form of robustness check in the regression (Abadie et al., 2004).

[19] In fact, a regression similar to Table 1 which explains cooking time and includes stove indicators suggests that those who use clean-fuel and coal stoves spend less time cooking than those who use traditional-biomass stoves. There is no statistically significant difference in cooking time for improved-biomass versus traditional-biomass.

Table 2a
County Averages: Fractions of Stove Users & Health / Other Characteristics.

County	N	Stoves				Characteristics				
		T.Bio	I.Bio	Coal	Clean	PCS	Age (yrs)	Income (1000 s)	Cooking (min/day)	Kitchen openings
Fuping	275	0.00	0.00	0.99	0.01	50.1	38	8.6	138	2.4
Heyang	217	0.03	0.01	0.96	0.00	50.7	37	4.5	139	1.9
Lintong	332	0.07	0.65	0.23	0.05	47.9	41	7.4	129	2.4
Yanchuan	256	0.71	0.00	0.29	0.00	48.2	45	1.7	140	2.0
Hancheng	196	0.00	0.00	0.96	0.04	51.4	39	8.5	156	1.0
Suizhou	263	0.02	0.92	0.03	0.03	46.1	41	9.2	145	1.7
Changyang	236	0.03	0.75	0.05	0.17	46.9	41	9.5	154	1.8
Tongcheng	116	0.28	0.10	0.57	0.04	47.1	39	22.2	125	1.8
Xiantao	245	0.02	0.60	0.30	0.08	48.7	39	8.3	117	2.3
Yicheng	336	0.00	0.47	0.51	0.02	47.2	39	8.7	142	2.2
Anji	242	0.09	0.88	0.00	0.04	49.9	47	12.9	119	1.5
Kaihua	164	0.01	0.68	0.00	0.31	50.1	45	10.9	125	1.4
Xianju	163	0.00	0.94	0.00	0.06	49.2	44	11.5	111	2.5
Chunan	221	0.10	0.81	0.00	0.09	47.5	50	8.0	141	2.1
Tongxiang	325	0.79	0.18	0.00	0.03	50.7	46	23.5	85	3.7
Total	3587	0.16	0.47	0.32	0.06	48.7	42	9.8	131	2.1

use ranges from 99% in Fuping county to 0% in the last 5 counties listed. Traditional-biomass stoves are not present in a number of counties but in 2 counties make up over 70% of stove use. Over 60% use improved-biomass stoves in 8 counties, but these stoves are less present in other counties. The clean-fuel or most efficient stoves are less common overall but are 17% of the stoves used in Changyang county and 31% in Kaihua county.

Asymmetric stove-type distributions across counties could imply the correlation of stoves with county characteristics — observed and unobserved. County averages vary for individual and household observed characteristics, plus for health outcomes that will reflect unobserved factors. Within Table 1, age affects health, e.g., while in Table 2a even its average varies across counties. Income and kitchen ventilation are statistically correlated with health in Table 1, and in Table 2a both the average income and the average number of kitchen openings vary across these counties. From Table 2a alone, it is quite plausible that correlations between the distributions of the stoves and the distributions of health-relevant characteristics may hinder the estimation of stove impact. Such correlations may arise at the county level due to agency decisions to target certain counties.

Correlations also may arise within any given county, due to choices made by households. Table 2b shows the highest village

Table 2b
Minimum and maximum village averages of health and other characteristics, by county.

County		PCS Index	Age 26–40	Age 41–55	Age >55	Has wash. Machine	Has inc. >12 k	Cooking Time	Has kit. openings 1	2	>2	Has open air kitch.	Is Smoker
Fuping	Min	48.05	0.30	0.11	0.00	0.33	0.00	116.30	0.00	0.00	0.05	0.00	0.13
	Max	56.24	0.75	0.41	0.28	0.73	0.30	173.04	0.28	0.68	0.96	0.05	0.32
Heyang	Min	48.95	0.47	0.00	0.00	0.04	0.00	116.96	0.00	0.43	0.00	0.00	0.09
	Max	52.49	0.91	0.38	0.23	0.67	0.29	169.63	0.48	0.97	0.17	0.09	0.21
Lintong	Min	44.90	0.32	0.17	0.00	0.31	0.03	110.95	0.00	0.17	0.00	0.00	0.07
	Max	52.12	0.61	0.46	0.29	0.80	0.29	147.59	0.54	0.55	0.82	0.48	0.27
Yanchuan	Min	44.35	0.19	0.11	0.10	0.00	0.00	115.78	0.00	0.69	0.00	0.41	0.17
	Max	53.95	0.71	0.56	0.35	0.15	0.11	187.50	0.28	1.00	0.16	1.00	0.42
Hancheng	Min	49.63	0.32	0.17	0.00	0.50	0.00	115.43	0.25	0.05	0.00	0.00	0.06
	Max	54.86	0.78	0.47	0.17	1.00	0.35	187.80	0.75	0.40	0.09	0.29	0.25
Suizhou	Min	43.08	0.35	0.07	0.00	0.00	0.00	115.37	0.04	0.13	0.00	0.00	0.00
	Max	48.97	0.93	0.52	0.32	0.11	0.43	183.13	0.86	0.64	0.39	0.13	0.57
Changyang	Min	44.90	0.35	0.08	0.00	0.00	0.04	121.03	0.15	0.12	0.00	0.00	0.16
	Max	49.64	0.79	0.41	0.35	0.41	0.41	195.29	0.72	0.68	0.36	0.21	0.45
Tongcheng	Min	42.66	0.25	0.00	0.00	0.00	0.00	94.90	0.33	0.30	0.06	0.00	0.05
	Max	52.04	0.93	0.56	0.10	0.50	0.40	159.06	0.55	0.50	0.33	0.00	0.31
Xiantao	Min	46.09	0.36	0.00	0.00	0.14	0.09	101.36	0.08	0.13	0.14	0.00	0.00
	Max	51.66	1.00	0.44	0.27	0.43	0.75	140.94	0.48	0.58	0.74	0.07	0.36
Yicheng	Min	42.63	0.32	0.14	0.00	0.00	0.00	113.83	0.00	0.40	0.00	0.00	0.08
	Max	50.89	0.69	0.50	0.29	0.21	0.58	182.00	0.36	0.92	0.33	0.04	0.27
Anji	Min	39.75	0.11	0.32	0.00	0.00	0.00	66.89	0.36	0.00	0.00	0.00	0.13
	Max	53.06	0.50	0.64	0.31	1.00	0.50	150.93	1.00	0.64	0.21	0.11	0.50
Kaihua	Min	47.88	0.22	0.20	0.07	0.00	0.08	91.00	0.32	0.19	0.00	0.00	0.08
	Max	51.31	0.46	0.58	0.32	0.07	0.52	143.04	0.72	0.60	0.17	0.00	0.25
Xianju	Min	46.82	0.00	0.00	0.00	0.00	0.00	72.38	0.00	0.00	0.00	0.00	0.00
	Max	52.02	1.00	1.00	0.67	0.22	1.00	145.00	0.67	1.00	1.00	0.00	0.50
Chunan	Min	42.18	0.04	0.14	0.25	0.00	0.00	125.07	0.07	0.21	0.07	0.00	0.21
	Max	50.33	0.41	0.63	0.52	0.07	0.30	171.96	0.64	0.54	0.71	0.00	0.44
Tongxiang	Min	46.19	0.19	0.19	0.03	0.23	0.29	55.41	0.00	0.00	0.16	0.00	0.08
	Max	53.80	0.53	0.47	0.34	0.93	1.00	111.85	0.29	0.63	1.00	0.00	0.35

Table 2c
Stove-adoption probit regressions (marginal effects).

Treated / Control	Clean / Traditional		Improved / Traditional		Clean / Improved		Clean / Coal		Improved / Coal		Traditional / Coal	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Age 26–40	0.03		−0.10**		0.05**		0.01		−0.02		0.06	
Age 41–55	−0.01		−0.05		0.01		−0.01		0.07		0.05	
Age >55	−0.05		−0.14**		−0.02		−0.08*		0.03		−0.04	
Age		−0.00		0.01**		0.00		0.02**		0.01*		0.02**
Age squared		0.00		−0.00**		−0.00*		−0.00**		−0.00		−0.00**
Male	0.06	0.04	0.06**	0.05*	0.04**	0.04**	0.07	0.06	−0.01	−0.00	−0.11*	−0.11*
Income >12,000	0.05**		0.02		0.05***		0.04		−0.01		−0.11*	
Income (1000 s)		0.00		0.00		0.00***		0.01**		−0.00		−0.02***
Income Squared		0.00		−0.00		−0.00*		−0.00**		−0.00		0.00
Washing Machine	0.11***	0.10***	−0.07***	−0.07***	0.14***	0.13***	0.09***	0.09***	−0.24***	−0.22***	−0.16***	−0.14***
TV	0.03	0.04	0.19***	0.17***	0.03	0.03	0.07	0.06	−0.07	−0.07	−0.22***	−0.21***
Cooktime (minutes)	−0.00**	−0.00***	−0.00	−0.00***	−0.00***	−0.00***	−0.00**	−0.00	0.00	0.00***	0.00***	0.00
Cooktime squared		0.00***		0.00***		0.00***		0.00		−0.00***		−0.00
Smoker	0.06	0.07*	−0.05	−0.05	−0.01	−0.01	−0.03	−0.03	−0.01	−0.01	0.13*	0.13*
Openings = 1	−0.04	−0.03	−0.21**	−0.23**	0.02	0.02	0.01	0.01	0.00	0.01	−0.00	−0.02
Openings = 2	−0.05	0.04	−0.21**	−0.22**	0.01	0.01	−0.03	−0.04	−0.03	−0.03	0.06	0.05
Openings > 2	−0.07	−0.05	−0.15	−0.14	0.02	0.01	−0.01	−0.01	0.04	0.05	−0.00	−0.00
Open-air kitchen	0.04	0.01	0.08	0.09*	0.03	0.03	0.02	0.01	0.07	0.06	0.05	0.03
Fuping	–	–	–	–	–	–	–	–	–	–	–	–
Heyang	–	–	–	–	–	–	–	–	–	–	−0.18**	−0.22**
Lintong	0.62***	0.71***	0.22***	0.23***	0.03	0.08*	0.08	0.09*	0.23***	0.22***	0.37***	0.35***
Yanchuan	–	–	–	–	–	–	–	–	–	–	0.55***	0.48***
Hancheng	–	–	–	–	–	–	−0.07	−0.07	–	–	–	–
Suizhou	–	–	0.27***	0.27***	0.05	0.09*	0.51***	0.51***	0.34***	0.35***	–	–
Changyang	–	–	0.22***	0.22***	0.29***	0.37***	0.71***	0.73***	0.29***	0.29***	0.35**	0.42***
Tongcheng	0.45***	0.48***	0.07*	0.09**	0.26**	0.34***	−0.02	−0.02	−0.34***	−0.32***	0.38***	0.39***
Xiantao	–	–	0.20***	0.20***	0.13***	0.21***	0.11**	0.13**	0.17***	0.17***	O	O
Yicheng	–	–	–	–	0.10*	0.14**	O	O	O	O	–	–
Anji	0.56***	0.49***	0.22***	0.23***	−0.03	−0.03	–	–	–	–	–	–
Kaihua	–	–	–	–	0.45***	0.48***	–	–	–	–	–	–
Xianju	–	–	–	–	0.06	0.10**	–	–	–	–	–	–
Chunan	0.87***	0.84***	0.20***	0.20***	0.22***	0.27***	–	–	–	–	–	–
Tongxiang	O	O	O	O	O	O	–	–	–	–	–	–
Pseudo R2	0.38	0.42	0.50	0.50	0.23	0.25	0.33	0.35	0.25	0.26	0.38	0.40
Max. Likelihood	−106	−98	−440	−434	−480	−473	−197	−193	−619	−614	−302	−294
Observations	417	417	1617	1617	1861	1861	700	700	1359	1359	767	767

O indicates the omitted county.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

average and the lowest village average for each characteristic by county, showing that dramatic differences can exist within-county too (and this surely extends to individual variation within any given village — noting that our analyses are at individual level). The statistics in the table suggest the potential for household and individual decisions in a county to generate a correlation between health-relevant characteristics and the possession of any stove. For instance, richer households could be more willing to adopt whatever new stoves are offered. Thus, even if agencies target poorer counties, the relatively less poor may receive those new stoves.

Considering Yanchuan, e.g., Table 2a suggests it lacked access to clean-fuel or improved-biomass stoves. On average, it seems poor, which may help to explain 71% traditional-biomass. Table 2b confirms that the poorest village in the county is poor, with nobody owning a washing machine or earning over 12,000 Yuan. Yet the richest village seems a bit wealthier and less poor households may be more likely to receive the new stoves. Age distribution varies a lot by village in this county too. All of this motivates analyses using individual, household, and county controls.

5.1.2. Stove-Adoption Regressions

The above emphasizes that agency and household decisions may lead stoves' allocations in different directions. For instance, top-down allocation could send cleaner stoves to poorer areas, yet

Table 3
Regression analysis of stove effects on PCS.

Stove pairs	#obs	(1)	(2)	(3)	(4)
Clean Fuel	59	1.69	2.00*	3.45***	2.57*
Traditional biomass	358	(1.17)	(1.18)	(1.27)	(1.33)
Improved biomass	1243	−1.04**	0.06	1.42*	0.65
Traditional biomass	374	(0.52)	(0.55)	(0.75)	(0.73)
Clean fuel	196	2.01***	1.85***	1.65**	0.55
Improved biomass	1665	(0.65)	(0.64)	(0.66)	(0.66)
Clean fuel	105	−1.40	−1.13	−0.41	−1.57
Coal	595	(0.89)	(0.90)	(1.06)	(1.04)
Improved biomass	952	−1.85***	−1.87***	−1.56**	−0.75
Coal	407	(0.53)	(0.53)	(0.61)	(0.59)
Traditional biomass	256	−2.04***	−2.16***	−1.39	-0.67
Coal	511	(0.67)	(0.68)	(0.85)	(0.80)
	Province	No	Yes	Yes[a]	Yes[a]
	County	No	No	Yes	Yes
	Chars.[†]	No	No	No	Yes

[a] Since they are bigger political units, which are made up of counties, the provinces' average impacts are being captured through the impacts of their counties.
[†] Household and individual characteristics: gender; continuous and quadratic age; continuous and quadratic income; washing machine ownership; tv ownership; smoker; kitchen openings (=1,=2, >2); whether the residence has an open air kitchen; and continuous and quadratic cooking time make up this specification.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

Table 4a
Balance for clean-fuel versus traditional biomass.

	Means	Means		PS* matching (m = 1)		Cov.** matching (m = 1)	
	Clean fuel	Trad'l biomass	t-test's p value	Trad'l biomass	t-test's p value	Trad'l biomass	t-test's p value
Age 26–40	0.56	0.39	0.01	0.46	0.27	0.63	0.46
Age 41–55	0.25	0.32	0.32	0.17	0.26	0.17	0.26
Age > 55	0.14	0.25	0.06	0.34	0.01	0.19	0.46
Male	0.37	0.30	0.28	0.44	0.46	0.32	0.57
Income > 12,000 Yuan	0.51	0.67	0.02	0.51	1.00	0.37	0.14
Own washing machine	0.58	0.57	0.90	0.41	0.07	0.36	0.02
Own tv	0.97	0.94	0.49	0.95	0.65	0.97	1.00
Cooking time (minutes/day)	99.88	99.79	0.99	108.39	0.42	110.34	0.30
Smoker	0.31	0.21	0.09	0.39	0.34	0.29	0.84
One kitchen openings	0.37	0.18	0.00	0.27	0.24	0.49	0.20
Two kitchen openings	0.31	0.23	0.19	0.39	0.34	0.34	0.70
More than two kitchen openings	0.29	0.59	0.00	0.31	0.84	0.17	0.13
Additional open air kitchen	0.03	0.01	0.04	0.03	1.00	0.03	1.00
Lintong	0.27	0.06	0.00	0.29	0.84	exact	–
Tongcheng	0.08	0.09	0.86	0.05	0.47	exact	–
Anji	0.15	0.06	0.01	0.05	0.07	exact	–
Chunan	0.32	0.06	0.00	0.47	0.09	exact	–
Tongxiang	0.17	0.72	0.00	0.14	0.61	exact	–

* Propensity-score matching.
** Covariate matching, exact (matches required to be in the same county).

bottom-up adoption could lead cleaner stoves to be used by richer households in those areas. That would leave ambiguous the overall relationship of cleaner stove ownership to income level. Thus, in stove-adoption regressions in Table 2c, we include county indicators plus individual and household characteristics. For the latter, we try both a categorical and a continuous specification.

In its first column, which compares possession of clean versus traditional-biomass stoves, Table 2c shows positive coefficients for income and ownership of washing machine indicators. This may appear to contradict Table 2a, where the counties with high clean-stove fractions have below-average income and, additionally, a relatively rich county mostly uses traditional stoves. However, Table 2c includes counties; thus, its income and washing-machine coefficients reflect household differences *in a given county*: within any county, those adopting clean-fuel are richer.

Sticking with a focus on income in Table 2c, we see positive effects for clean-fuel in all its stove comparisons. That is what we might expect: richer households receive the cleanest stoves. Even an apparent contradiction in Table 2c supports the theory that richer households are more likely to adopt new stoves. The negative sign for traditional-biomass, when compared with coal, could easily reflect the discussion above that for reasons distinct from health the new stoves that agencies introduced in some locations were the coal stoves. These are not the cleanest stoves but they were the new stoves introduced and we might well expect the less poor to end up with them.

Comparison with Table A.2 in the Appendix (similar to Table 2c but excluding counties, thus blending within- with across-county differences, as in our tests of covariate balance below) suggests that, controlling for other factors, indeed the counties with more clean stoves are poorer. For the same first column as Table 2c, i.e., comparing

Table 4b
Balance for traditional biomass versus coal.

	Means	Means		PS* matching (m = 1)		Cov.** matching (m = 1)	
	Trad'l biomass	Coal	t-test's p value	Coal	t-test's p value	Coal	t-test's p value
Age 26–40	0.45	0.57	0.00	0.43	0.79	0.46	0.72
Age 41–55	0.32	0.23	0.01	0.32	0.93	0.30	0.63
Age > 55	0.19	0.13	0.03	0.18	0.82	0.18	0.82
Male	0.32	0.23	0.01	0.32	1.00	0.30	0.63
Income > 12,000 Yuan	0.04	0.13	0.00	0.02	0.43	0.04	1.00
Own washing machine	0.07	0.29	0.00	0.07	0.87	0.09	0.51
Own tv	0.71	0.92	0.00	0.74	0.49	0.81	0.01
Cooking time (minutes/day)	141.25	130.75	0.00	144.30	0.42	134.94	0.07
Smoker	0.26	0.16	0.00	0.29	0.43	0.24	0.68
One kitchen openings	0.11	0.18	0.01	0.14	0.35	0.11	0.78
Two kitchen openings	0.79	0.63	0.00	0.76	0.46	0.83	0.18
More than two kitchen openings	0.09	0.17	0.00	0.10	0.65	0.06	0.24
Additional open air kitchen	0.62	0.14	0.00	0.64	0.58	0.67	0.23
Heyang	0.02	0.41	0.00	0.03	0.59	exact	–
Lintong	0.09	0.15	0.02	0.12	0.31	exact	–
Yanchuan	0.71	0.14	0.00	0.71	1.00	exact	–
Changyang	0.03	0.02	0.53	0.02	0.24	exact	–
Tongcheng	0.13	0.13	0.99	0.11	0.59	exact	–
Xiantao	0.02	0.14	0.00	0.01	0.70	exact	–

* Propensity-score matching.
** Covariate matching, exact (matches required to be in the same county).

Table 4c
Balance for clean fuel versus coal.

	Means	Means		PS* matching (m = 1)		Cov.** matching (m = 1)	
	Clean fuel	Coal	t-test's p value	Coal	t-test's p value	Coal	t-test's p value
Age 26–40	0.67	0.53	0.01	0.69	0.77	0.79	0.04
Age 41–55	0.23	0.27	0.37	0.17	0.30	0.15	0.16
Age > 55	0.04	0.10	0.03	0.06	0.52	0.01	0.18
Male	0.31	0.26	0.22	0.30	0.88	0.20	0.06
Income > 12,000 Yuan	0.41	0.18	0.00	0.31	0.15	0.31	0.15
Own washing machine	0.50	0.45	0.26	0.58	0.27	0.46	0.49
Own tv	0.99	0.96	0.15	0.99	1.00	1.00	0.32
Cooking time (minutes/day)	115.38	138.75	0.00	116.1	0.92	122.38	0.26
Smoker	0.19	0.17	0.7	0.25	0.32	0.16	0.59
One kitchen openings	0.36	0.31	0.34	0.22	0.02	0.25	0.07
Two kitchen openings	0.36	0.41	0.35	0.43	0.33	0.49	0.07
More than two kitchen openings	0.23	0.18	0.28	0.34	0.07	0.25	0.75
Additional open air kitchen	0.10	0.05	0.1	0.16	0.15	0.10	1.00
Lintong	0.15	0.13	0.52	0.14	0.85	exact	–
Hancheng	0.08	0.32	0.00	0.07	0.79	exact	–
Suizhou	0.09	0.01	0.00	0.03	0.08	exact	–
Changyang	0.37	0.02	0.00	0.40	0.67	exact	–
Tongcheng	0.05	0.11	0.05	0.01	0.10	exact	–
Xiantao	0.19	0.12	0.06	0.28	0.14	exact	–
Yicheng	0.08	0.29	0.00	0.08	1.00	exact	–

* Propensity-score matching.
** Covariate matching, exact (matches required to be in the same county).

clean-fuel to traditional-biomass stoves in a specification without counties, in Table A.2 neither income nor asset dummies are significant. For improved-biomass versus traditional, in Table A.2, all of the income and assets coefficients in columns (2a,b) are negative and significant, suggesting downward bias in estimated impacts. Thus, potential determinants' associations with stoves differ when not conditioning on counties. This highlights the potential importance of control for political units in estimating stove impact.

Age, an important health determinant, does not stand out within Table 2c (or in Table A.2). Income and wealth stand out, while gender is statistically significant in columns (2a) and (2b) for improved-biomass stoves compared to traditional. Again highlighting critical county differences, gender vanishes in Table A.2. Further, in the same column, i.e. same stoves pair, the significance of the number of kitchen openings is reversed in Table A.2 (versus within-county, in Table 2c).

5.2. Regression Estimates of Stove Iimpacts (Increasing Controls in Steps)

Table 3 uses regressions to link our PCS or health outcome with different types of stoves. Column (1) includes no variables at all as controls. Column (2) adds province dummy variables. Column (3) instead employs dummy variables for counties — significantly smaller political units. Column (4) retains county dummy variables and adds individual and household characteristics, using all of the continuous variables we have in their continuous form, including squared terms. Each row in Table 3 presents results for all four specifications for one of the stove comparisons.

Summarizing, a comparison of columns 1–4 shows that the covariates shift the estimates. Of the six conclusions, i.e., one per row, that we might take away from the results in column (1) which includes no controls, five of them would not be the conclusions that we would take from the results within column (4). Sometimes the inclusion of political units changes the estimates. Sometimes the inclusion of individual and household characteristics does. Sometimes both do. These are not arbitrary shifts but, instead, are consistent with all of the facts presented above.

Looking within the 1st row, comparison of columns (2) and (3) with (1) suggests that the most efficient of the stoves, the clean-fuel, were allocated to less healthy provinces and counties. Perhaps that is due to poverty, for instance, but we cannot know which county features drive this. Concluding from (3) versus from (1) shifts toward a finding that clean-fuel stoves improve health relative to traditional-biomass stoves. As noted above though, whatever occurs *across* counties we might expect that *within* any county the richer and perhaps healthier households adopt more. Comparing (4) to (3) for this stove pair is supportive of that. The impact coefficient is lower.[20]

This pattern holds for the 2nd-row comparison of improved biomass to traditional stoves. A significantly more positive impact of the improved stoves is suggested by column (3) than (1), although in this case adding the province and then county variables eliminates an initial estimate in (1) of health *damages* from the improved-biomass stove, which would be a surprising result.[21] Comparing (4) to (3) again supports our hypothesis from above that richer, healthier households within a county are more likely to adopt a stove. For this row, the effect in (4) is not significant. Yet as in the first row, the estimate in (4) with all of our controls is higher than in (1) with none.

Considering coal stoves, the interesting results in Table 3 are in the fifth and sixth rows, i.e., comparisons of coal with improved-biomass (fifth row) and traditional-biomass (sixth row). For both these stove comparisons, it appears that the coal stoves we examine in our sample went to: counties that are healthier on average; and, comparing column (4) with (3), in particular households who are healthier on

[20] It is possible that variables omitted in (4), such as other characterizations of wealth, could still bias the estimates. We conducted a placebo check, substituting the physical component summary dependent variable with a dummy variable which indicates whether individuals had an illness that changed the kind or amount of food eaten (which stoves should not affect). In contrast to the PCS health result, clean-fuel stoves had no significant estimated effect.

[21] No impact in the 1st row of (1), versus estimated damage in the 2nd row, suggests that improved-biomass owners are worse off than clean-fuel owners. That is supported by the estimated gain from clean-fuel in the third row of (1) given no such effect in (4) with all our controls. That is also supported by comparing characteristics within Table 1.

Table 5
Matching analysis of stove effects on PCS.

Treated stove	Clean	Impr.	Clean	Clean	Impr.	Trad.
Control Stove	Trad.	Trad.	Impr.	Coal	Coal	Coal
N treated	59	1243	196	105	952	256
N control	358	374	1665	595	407	511
Estimate	ATT	ATC	ATT	ATT	ATC	ATT
Specification A						
(1) Covariate matching (m = 1, exact matching by county)	5.28***	1.95*	1.51†	−0.78	−0.83	−0.99
	(1.87)	(1.15)	(0.93)	(1.99)	(0.86)	(1.32)
(2) Covariate matching (m = 2, exact matching by county)	3.66**	1.53	1.60**	−1.64	−1.59**	−1.38
	(1.59)	(1.03)	(0.80)	(1.53)	(0.78)	(1.13)
(3) Propensity score matching (m = 1)	6.36**	1.26	0.32	−3.75**	−1.49	−0.78
	(3.04)	(1.07)	(1.13)	(1.86)	(1.03)	(1.63)
(4) Propensity score matching (m = 2)	4.86*	2.11**	0.10	−3.56**	−0.85	−2.12
	(2.76)	(1.02)	(1.03)	(1.74)	(0.94)	(1.44)
(5) Propensity score matching (m = 1, with caliper = 0.1)	5.91**	1.26	0.56	−3.75**	−1.49	−0.78
	(2.79)	(1.09)	(1.05)	(1.78)	(1.03)	(1.55)
(6) Propensity score matching (m = 2, with caliper = 0.1)	5.04**	2.11**	0.09	−3.56**	−0.85	−2.12
	(2.42)	(1.00)	(1.00)	(1.63)	(0.93)	(1.45)
Specification B						
(7) Covariate matching (m = 1, exact matching by county)	3.20*	1.56	1.14	−0.48	−0.72	−2.22*
	(1.68)	(1.10)	(0.97)	(1.74)	(0.85)	(1.23)
(8) Covariate matching (m = 2, exact matching by county)	2.57*	1.46	1.43*	−1.05	−0.89	−1.97*
	(1.42)	(1.03)	(0.83)	(1.52)	(0.80)	(1.14)
(9) Propensity score matching (m = 1)	6.83	1.21	0.01	−2.77	−0.57	−0.93
	(4.67)	(1.24)	(1.07)	(2.06)	(1.01)	(1.52)
(10) Propensity score matching (m = 2)	7.36*	1.45	0.40	−2.81	−0.97	−1.22
	(3.76)	(1.13)	(0.97)	(1.81)	(0.97)	(1.40)
(11) Propensity score matching (m = 1, with caliper = 0.1)	4.89	1.21	0.22	−2.77†	−0.66	−0.93
	(3.45)	(1.17)	(1.08)	(1.72)	(1.00)	(1.56)
(12) Propensity score matching (m = 2, with caliper = 0.1)	5.52*	1.45	0.54	−2.81*	−0.94	−1.22
	(3.34)	(1.16)	(0.95)	(1.59)	(0.97)	(1.38)

Specification A includes indicators for male, age (26–40, 41–55, >55), income more than 12000 Yuan, washing machine ownership, tv ownership, smoker openings in kitchen (1,2, >2), whether the residence has an open air kitchen, county dummy variables, and the number of minutes spent cooking per day.
Specification B substitutes continuous measures of age, income, and cooking time in Specification A and includes their quadratic terms.
Standard errors in parentheses. Bootstrapped standard errors from 1000 repetitions used in propensity score matching estimates.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.
† $p < 0.11$.

average within these counties (specifically, within the counties employed in the regressions, i.e., those for which we had sufficient usage of each of the stoves). The coefficients in (4), both suggesting no impact of stoves, differ significantly from those in (1) that suggested coal stoves are healthier: initial, highly surprising damages in (1) are eliminated.

5.3. Matching Estimates of Stove Impacts

5.3.1. Improved balances

In Table 3, in our efforts to best account for the influences of all of the observed variables, we used the few continuous variables in their continuous form and included their squared terms. Given few observations per stoves comparison, though, that specification lowered match quality. Looking ahead, we will focus in Table 5 on the results of the linear matching specification (‘A’).

For that specification, Tables 4a–4c show tests of balance for stove comparisons of interest. We can see that the propensity-score matching produces matched samples with decidedly smaller average characteristics differences than between improved-stove owners and all of the untreated. After matching, the great majority of the differences are no longer even statistically significant. The same holds when applying covariate matching and forcing comparisons among stove users in the same county. It is good to see that even when imposing a within-county restriction, other variables still improve in balance, even if sometimes less than when using the propensity score.

5.3.2. Matching Confirms Regressions Estimates using Controls

Comparing Tables 3 and 5 suggests that our core results are not driven by functional form. Specifically, the patterns of the results in Table 5 support the conclusions suggested by Table 3. We focus on consistency between Tables 5 and 3's column (4) that uses all of the controls. Within Table 5, as noted we will focus on the results from Specification A — not using quadratic versions of continuous variables — because the balance for the covariates is better than within B.

Taken as a whole these results, which make use of all the county and individual controls, contrast with Table 3's column (1), in showing that clean-fuel improves upon traditional biomass. Further, the matching result is quite robust. A bias adjustment with the covariates after matching, for instance, yields coefficient (6.23) and statistical significance similar to Specification A row 1. Adding an indicator for multiple stoves to the bias adjustment also produces a coefficient (6.14) and significance similar to Table 5. Omitting cooking time as a covariate again yields the same.

The evidence for benefits of improved-biomass stoves, relative to traditional-biomass, is decidedly less clear in Tables 5 and 3 column (4), however. Much in the same vein, though, certainly the negative coefficient in column (1) of Table 3 is thoroughly rejected, using controls, and we add that matching for FEV1 in Table A.3 supports the result for PCS in clean-fuel versus traditional-biomass while suggesting benefits from improved-biomass stoves versus traditional.

Concerning the comparisons with coal stoves, again the interesting results in Table 3 are in the comparison with biomass stoves, where initial estimates of health benefits from coal in (1) are rejected in (4) for each of the biomass stoves. Matching results clearly support that rejection. Overwhelmingly, the matching comparisons making use of all of the controls in a different form find no significant impact. That may not correct for all possible biases from the allocation of the coal stoves. However, these corrections clearly reject the initial spurious estimates of coal gains, demonstrating that the inclusion of controls has an important effect that is robust to specification.

6. Conclusion

We used unique data collected in China to demonstrate the importance of accounting for nonrandom distributions of stove types when evaluating the impacts of those stoves upon health. Policies encouraged new stoves, clean and dirty, with allocations that varied over time and space. County differences and within-county household differences led relevant characteristics, directly or indirectly observed, to be correlated with both stoves-adoption decisions and health outcomes. Failures to document and address differences in such characteristics, across stove-owner groups, generated biases in impacts estimates. In our case, the dirtier stoves were possessed by healthier households, masking cleaner stoves' benefits and falsely suggesting benefits from dirtier stoves.

One reason that the health effects of stoves were initially masked in our analyses is that owners of coal stoves, for instance, were richer — a household difference correlated with health. At least as important were political units, like counties, which differed in both stoves and health. Controlling for counties plus individual and household characteristics affected impact estimates, for instance eliminating surprising conclusions. Yet unobservable differences still could remain, of course, and thus, generally, we encourage all approaches to eliminating confounding factors.

The importance of documenting such interventions, in order to be able to control to some extent for who received what stove intervention, highlighted the opportunity that is provided by our quite large household dataset for China. More common for this type of study might be a lack of such survey data, yet controlled comparisons also can arise through experimental design, such as randomization. While randomization is not always feasible for a suite of reasons, in situations when it does not occur our approach and results still suggest value from simple documentation of all the interventions and outcomes as part of informing improvements in such policies over time.

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Table A.1
(Analogous to Table 1 but for a different indicator of health). Determinants of Forced Expiratory Volume 1 (excluding stove indicators).

	(1) OLS coefficients	Std.errors	(2) OLS coefficients	Std.errors
Age 26–40	−0.08	0.05		
Age 41–55	−0.29***	0.06		
Age > 55	−0.87***	0.07		
Age			0.02***	0.01
Age squared			−0.00***	0.00
Male	0.56***	0.04	0.56***	0.04
Income > 12,000 Yuan	0.00	0.04		
Income (1000 s Yuan)			−0.00	0.00
Income squared			0.00	0.00
Own washing machine	0.01	0.04	−0.01	0.04
Own tv	0.09*	0.05	0.07	0.05
Cooking time (minutes/day)	0.00	0.00	−0.00	0.00
Cooking time squared			0.00	0.00
Smoker	0.10**	0.05	0.10*	0.05
One kitchen openings	0.02	0.07	0.03	0.07
Two kitchen openings	0.02	0.07	0.03	0.07
More than two kitchen openings	0.01	0.07	0.02	0.07
Additional open air kitchen	-0.07	0.07	-0.04	0.07
Heyang	-0.42***	0.07	-0.40***	0.07
Lintong	−0.30***	0.07	−0.28***	0.07
Yanchuan	0.63***	0.09	0.61***	0.07
Hancheng	0.10	0.07	0.13*	0.09
Suizhou	−0.23***	0.06	−0.23***	0.06
Changyang	−0.04	0.08	−0.02†	0.08
Tongcheng	−0.32***	0.08	−0.31***	0.08
Xiantao	−0.25***	0.07	−0.24***	0.07
Yicheng	0.09	0.06	0.10	0.06
Anji	-1.13***	0.07	-1.07***	0.07
Kaihua	-0.35***	0.08	-0.33***	0.08
Xianju	-0.44***	0.09	-0.45***	0.09
Chunan	-0.27***	0.07	-0.22***	0.07
Tongxiang	-0.60***	0.07	-0.59***	0.07
Constant	2.67***	0.11	2.50***	0.18
Adjusted R-squared	0.45		0.46	
Root MSE	0.55		0.55	
Observations	1921		1921	

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

Table A.2
(Analogous to Table 2c but without counties)
Stove-adoption probit regressions (marginal effects)

Treated Control	Clean Traditional		Improved Traditional		Clean Improved		Clean Coal		Improved Coal		Traditional Coal	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Age 26–40	0.05		−0.10**		0.05*		0.07		0.03		0.06	
Age 41–55	−0.01		−0.08		−0.00		0.01		0.09*		0.11	
Age >55	−0.04		−0.17***		−0.03		−0.07		0.09		0.06	
Age		−0.00		0.01		0.00		0.02***		0.01		0.02**
Age squared		0.00		−0.00**		−0.00		−0.00***		−0.00		−0.00**
Male	0.01	0.01	0.03	0.03	0.03*	0.03	0.09**	0.07	−0.05	−0.05	−0.08	−0.08
Income >12,000	−0.05		−0.24***		0.05***		0.13***		−0.02		−0.06	
Income (1000 s)		−0.01***		−0.02***		0.00***		0.01***		−0.00		−0.01**
Income squared		0.00**		0.00***		−0.00		−0.00**		−0.00		0.00
Washing machine	0.05	0.07**	−0.13***	−0.11***	0.04***	0.04**	0.03	0.03	−0.19***	−0.18***	−0.17***	−0.14***
TV	0.07	0.07	0.18***	0.20***	0.04***	0.05	0.08	0.08	−0.13**	−0.13**	−0.27***	−0.26***
Cooktime (minutes)	−0.00	−0.00***	0.001***	0.00**	−0.00***	−0.00***	−0.00***	−0.00**	0.00***	0.00***	0.00***	−0.00
Cooktime squared		0.00***		−0.00		0.00***		0.00		−0.00**		0.00
Smoker	0.09	0.07	−0.02	−0.02	−0.01	−0.01	−0.04	−0.04	0.07*	0.07*	0.08	0.08
Openings = 1	−0.04	−0.07	−0.12	−0.14	0.03	0.02	0.15**	0.14**	−0.09	−0.08	0.14	0.14
Openings = 2	−0.08	−0.08	−0.17*	−0.18*	0.00	0.00	0.10*	0.10	−0.23***	−0.23***	0.15	0.16
Openings > 2	−0.23*	−0.24**	−0.29***	−0.29***	0.00	0.00	0.17**	0.17**	−0.11	−0.10	0.17	0.20
Open − air kitchen	0.08	0.07	0.14**	0.14**	0.01	0.02	0.13**	0.13**	0.15***	0.14**	0.45***	0.42***
Pseudo R2	0.11	0.19	0.23	0.23	0.12	0.12	0.11	0.11	0.06	0.07	0.25	0.26
Max. likelihood	−151	−139	−677	−677	−554	−550	−264	−262	−779	−775	−365	−360
Observations	417	417	1617	1617	1861	1861	700	700	1359	1359	767	767

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

Table A.3
(Analogous to Table 5 but for a different indicator of health)
Matching analysis of stove effects on forced expiratory volume 1

Treated stove Control stove	Clean Trad.	Impr. Trad.	Clean Impr.	Clean Coal	Impr. Coal	Trad. Coal
N treated	29	630	102	58	455	180
N control	186	194	826	338	227	296
Estimate	ATT	ATC	ATT	ATT	ATC	ATT
Specification A						
(1) Covariate matching (m = 1, exact matching by county)	0.21*	0.41***	0.11	0.09	0.05	−0.10
	(0.11)	(0.15)	(0.08)	(0.15)	(0.07)	(0.10)

Specification A includes indicators for male, age (26-40, 41-55, >55), income more than 12000 Yuan, washing machine ownership, tv ownership, smoker openings in kitchen (1,2, >2), whether the residence has an open air kitchen, county dummy variables, and the number of minutes spent cooking per day.
Standard errors in parentheses.
*** $p < 0.01$.
* $p < 0.1$.

References

Abadie, A., Imbens, G.W., 2002. Simple and bias-corrected matching estimators for average treatment effects. NBER Technical Working Paper no. 283.
Abadie, A., Drukker, D., Herr, J.L., Imbens, G.W., 2004. Implementing matching estimators for average treatment effects in Stata. The Stata Journal 4 (3), 290–311.
Andam, K., Ferraro, P., Pfaff, A., Robalino, G.J., Sanchez-Azofeifa, A., 2008. Measuring the effectiveness of protected-area networks in reducing deforestation. PNAS 105 (42), 16089–16094.
Angrist, J.D., Krueger, A.B., 1999. Empirical Strategies in Labor Economics. Industrial Relations Section, Dept. of Economics, Princeton University, Princeton, N.J.
Baumgartner, J., Schauer, J., Ezzati, M., Lin, L., Cheng, C., Patz, J., Bautista, L., 2011. Indoor air pollution and blood pressure in adult women living in rural China. Environmental Health Perspectives 119, 1390–1395.
Bensch, G., Peters, J., 2012. A recipe for success? Randomized free distribution of improved cooking stoves in Senegal. Ruhr Economic Papers #325 RWI. http://dx.doi.org10.4419/86788374.
Boy, Erick, Bruce, Nigel, Delgado, Hernan, 2002. Birth weight and exposure to kitchen wood smoke during pregnancy in rural guatemala. Environmental Health Perspectives 110 (11), 109–114.
Bruce, Nigel, Neufeld, Lynnette, Boy, Erick, West, Chris, 1998. Indoor biofuel air pollution and respiratory health: the role of confounding factors among women in Highland Guatemala. International Journal of Epidemiology 27, 454–458.
Bruce, Nigel, McCracken, John, Albalak, Rachel, Schei, Morten, Smith, Kirk R., Lopez, Victorina, West, Chris, 2004. Impact of improved stoves, house construction, and child location on levels of indoor air pollution exposure in young Guatemalan children. Journal of Exposure Analysis and Environmental Epidemiology 14, S26–S33.
Butrick, E., Peabody, J., Solon, O., DeSalvo, K., Quimbo, S., 2008. "A Comparison of Biomarkers and General Self Reported Health Status From the Quality Improvement Demonstration Study", Mimeo.
Dasgupta, S., Huq, M., Khaliquzzaman, M., Pandey, K., Wheeler, D., 2006. Indoor air quality for poor families: new evidence from Bangladesh. Indoor Air 16, 426–444.
Dehejia, R., Wahba, S., 1999. Causal effects in nonexperimental studies: re-evaluating the evaluation of training programs. Journal of the American Statistical Association 94, 1053–1062.
DeSalvo, K., Jones, T., Peabody, J., McDonald, J., Fihn, S., Fan, V., He, J., Muntner, P., 2009. Health care expenditure prediction with a single item, self-rated health measure. Medical Care 47 (4), 440–447.
Dix-Cooper, L., Eskenazi, B., Romero, C., Balmes, J., Smith, K.R., 2012. Neurodevelopmental performance among school age children in rural Guatemala is associated with prenatal and postnatal exposure to carbon monoxide, a marker for exposure to woodsmoke. NeuroToxicology 33, 246–254.
Edwards, Rufus D., Liu, Yaping, He, Gongli, Yin, Zheng, Sinton, Jonathan, Peabody, John, Smith, Kirk R., 2007. Household CO and PM measured as part of a review of China's national improved stove program. Indoor Air 17 (3), 189–203.
Ezzati, Majid, Kammen, Daniel, 2001a. Indoor air pollution from biomass combustion and acute respiratory infections in Kenya: an exposure-response study. Lancet 358, 619–624.
Ezzati, Majid, Kammen, Daniel, 2001b. Quantifying the effects of exposure to indoor air pollution from biomass combustion on acute respiratory infections in developing countries. Environmental Health Perspectives 109 (5), 481–488.
Ezzati, M., Saleh, H., Kammen, D., 2000. The contributions of emissions and spatial microenvironments to exposure to indoor air pollution from biomass combustion in Kenya. Environmental Health Perspectives 108 (9), 833–839.

Ezzati, M., Rodgers, A.D., Lopez, A.D., Murray, C.J.L. (Eds.), 2004. Comparative Quantification of Health Risks: Global and Regional Burden of Disease due to Selected Major Risk Factors. World Health Organization, Geneva.
Hanna, R., Duflo, E., Greenstone, M., 2012. Up in smoke: the influence of household behavior on the long-run impact of improved cooking stoves. MIT Department of Economics Working Paper No. 12–10.
Heckman, J.J., Smith, J.A., 1995. Assessing the case of social experiments. Journal of Economic Perspectives 9 (2), 85–110.
Heckman, J.J., Ichimura, H., Todd, P., 1997. Matching as an econometric evaluation estimator: evidence from evaluating a job training program. The Review of Economic Studies 64, 605–654.
Hill, J.L., Brooks-Gunn, J., Waldfogel, J., 2003. Sustained effects of high participation in an early intervention for low-birth-weight premature infants. Developmental Psychology 39 (4), 730–744.
IARC, 2010. Household Use of Solid Fuels and High Temperature Frying, vol. 95. IARC monographs on the Evaluation of Carcinogenic Risks to Humans, International Agency for Research on Cancer, WHO, Lyon.
IEA, 2010. World Energy Outlook 2010. International Energy Agency, Paris.
Lam, C., Gandek, B., Ren, X., Chan, M., 1998. Tests of scaling assumption and construct validity of the Chinese (HK) Version of the SF-36 health survey. Journal of Clinical Epidemiology 51 (11), 1139–1147.
Lam, C., Tse, E., Gandek, B., Fong, D., 2005. The SF-36 summary scales were valid, reliable, and equivalent in a Chinese population. Journal of Clinical Epidemiology 58, 815–822.
Lim, et al., 2012. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study. The Lancet 380, 2224–2260.
Lin, H., Ezzati, M., Murray, M., 2007. Tobacco smoke, indoor air pollution and tuberculosis: a systematic review and meta-analysis. PLoS Medicine 4, 1–17.
McCracken, J.P., Smith, K.R., Diaz, A., Mittleman, M.A., Schwartz, J., 2007. Chimney stove intervention to reduce long-term wood smoke exposure lowers blood pressure among Guatemalan women. Environmental Health Perspectives 115 (7), 996–1001.
Mishra, Vinod, Dai, Xiaolei, Smith, Kirk, Mika, Lasten, 2004. Maternal exposure to biomass smoke and reduced birth weight in Zimbabwe. Annals of Epidemiology 14 (1), 740–747.
Mobarak, M., Hildemann, L., Wise, P., 2011. Marketing cook-stoves to address indoor air pollution in Bangladesh. Project description available http://www.som.yale.edu/faculty/am833/Stoves.htm.
Morgan, S., Harding, D., 2006. Matching estimators of causal effects: prospects and pitfalls in theory and practice. Sociological Methods & Research 35 (1), 3–60.
Moshammer, Hanns, Hutter, Hans-Peter, Neuberger, Manfred, 2006. Gas cooking and reduced lung function in school children. Atmospheric Environment 40, 3349–3354.
Mueller, V., Pfaff, A., Peabody, J., Liu, Y., Smith, Kirk R., 2011. Demonstrating bias and improved inference for stoves' health benefits. International Journal of Epidemiology 40 (6), 1643–1651.
Pattanayak, S., Pfaff, A., 2009. Behavior, environment, and health in developing countries: evaluation and valuation. Annual Review of Resource Economics 1, 183–217.
Peabody, J., Riddell, T., Smith, K.R., Liu, Y., Zhao, Y., Jianghui, G., Milet, M., Sinton, J., 2005. Indoor air pollution in rural China: cooking fuels, stoves, and health status. Archives of Environmental and Occupational Health 60 (2), 1–10.
Peabody, J., Nordyke, R., Tozija, F., Luck, J., Munoz, J., Sunderland, A., DeSalvo, K., Ponce, N., McCulloch, C., 2006. Quality of care and its impact on population health: a cross-sectional study from Macedonia. Social Science & Medicine 62, 2216–2224.
Pfaff, A., Robalino, J., Sanchez-Azofeifa, G.A., Andam, K.S., Ferraro, P.J., 2009. Park location affects forest protection: land characteristics cause differences in park impacts across Costa Rica. The B.E. Journal of Economic Analysis & Policy 9, 1–24.
Pitt, Mark, Rosenzweig, Mark, Hassan, Md. Nazmul, 2006. Sharing the burden of disease: gender, the household division of labor and the health effects of indoor air pollution in Bangladesh and India," presented at the 2006 Stanford Institute for Theoretical Economics Summer Workshop.
Pokhrel, A., Bates, M., Verma, S., Joshi, H., Sreeramareddy, C., Smith, K.R., 2010. Tuberculosis and indoor biomass and kerosene use in Nepal: a case-control study. Environmental Health Perspectives 118, 558–564.
Pope, D., Mishra, V., Thompson, L., Siddiqui, A., Rehfuess, E., Weber, M., Bruce, N., 2010. Risk of low birth weight and stillbirth associated with indoor air pollution from solid fuel use in developing countries. Epidemiological Reviews 32, 70–81.
Robalino, J., Pfaff, A., 2013. Ecopayments and deforestation in Costa Rica: a nationwide analysis of PSA's initial years. Land Economics 89, 432–448.
Rosenbaum, P., Rubin, D., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), 41–55.
Sinton, Jonathan E., Smith, Kirk R., Peabody, John W., Liu, Yaping, Edwards, Rufus, Milet, Meredith, Gan, Quan, Yin, Zheng, 2004. Improved Household Stoves in China: An Assessment of the National Improved Stove Program (NISP). Shell Foundation, London (http://ehs.sph.berkeley.edu/HEM/hem/China%Stoves/Presentations/3.USA-%20Kirk%20Smith/ChinaStoves.Final%20report.2004.pdf).
Smith, K.R., 1993. Fuel combustion, air pollution exposure, and health: situation in developing countries. Annual Review of Energy & Environment 18, 529–566.
Smith, K.R., Gu, S.H., Huang, K., Qiu, D.X., 1993. 100 million improved stoves in China: how was it done? World Development 21 (6), 941–961.
Smith, Kirk R., Mehta, Sumi, Maeusezahl-Feuz, Mirjam, 2004. Indoor smoke from household solid fuels. In: Ezzati, M., Rodgers, A.D., Lopez, A.D., Murray, C.J.L. (Eds.), Comparative Quantification of Health Risks: Global and Regional Burden of Disease due to Selected Major Risk Factors, vol. 2. World Health Organization, Geneva, pp. 1435–1493.
Smith, Kirk R., Bruce, Nigel, Arana, Byron, 2006. "RESPIRE — the Guatemala Randomized Intervention Trial," Symposium M3 at the ISEE/ISEA Annual Conference, Paris. Epidemiology 17 (6), S44–S46 (Suppl. November).
Velema, J., Ferrera, A., Figueroa, M., Bulnes, R., Toro, L., De Barahona, O., Claros, J., Melchers, W., 2002. Burning wood in the kitchen increases the risk of cervical neoplasia in hpv-infected women in Honduras. International Journal of Cancer 97, 536–541.
Ware, J.E., Kosinski, M., Keller, S.D., 1995. SF-12: How to Score the SF-12 Physical and Mental Health Summary Scales. The Health Institute, New England Medical Center, Boston, Mass.
Wong, G., Brunekreef, B., Ellwood, P., Anderson, H., Innes Asher, M., Crane, J., Lai, C., for the ISAAC Phase Three Study Group, 2013. Cooking fuels and prevalence of asthma: a global analysis of phase three of the International Study of Asthma and Allergies in Childhood (ISAAC). The Lancet, Published online: http://dx.doi.org/10/1016/S2213-2600(13)70073-0.
Zhang, J., Smith, K.R., 2007. Household air pollution from coal and biomass fuels in China: measurements, health impacts, and interventions. Environmental Health Perspectives 115 (6), 848–855.