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Health impacts of cooking fuel choice in rural China

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Abstract

This study investigated the impact of cooking fuel choice on the health of elderly people, as measured by activities of daily living, using micro survey data from the China Health and Retirement Longitudinal Study 2015. In contrast to previous studies, our focus on activities of daily living allows for a more comprehensive analysis of health outcomes than diagnoses or doctor visits. Propensity score matching and an endogenous switching regression model were used to address potential selection biases. We found a strong and positive effect of using non-solid cooking fuels on an individual's ability to cope with daily activities, with substantially greater effects on female and older respondents. Our results highlight the need to support energy transition in rural households to non-solid fuels for cooking. We also discuss potential policies to facilitate energy transition in rural China.

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1. Introduction

A transition in energy for cooking is ongoing in many developing countries, but approximately three billion people in the world still do not have access to non-solid fuels for cooking, such as electricity and gas (World Health Organization, 2018). In China alone, the number of people relying on biomass for cooking in 2015 and Imelda, 2018 was over 300 and 240 million, respectively (International Energy Agency, 2017; International Energy Agency, 2019). Progress in energy transition in rural areas is much slower than in urban areas (Alem et al., 2016; Malakar et al., 2018), which is leading to attempts by policymakers to encourage the household adoption of non-solid fuels for cooking to address environmental problems such as deforestation and land degradation (Ekholm et al., 2010; Wang et al., 2017b) as well as public health concerns (Oluwole et al., 2012).

Compared to solid fuels such as coal, wood and other biomasses, non-solid fuels are often viewed as clean and less harmful to human health (Edwards and Langpap, 2012). Literature shows that the use of solid fuels increases the likelihood of low birth weight, respiratory infections and neonatal death in babies (Edwards and Langpap, 2012; Epstein et al., 2013). For adults, indoor air pollution from solid fuels also raises the probability of coughing and breathing difficulties (Jagger and Shively, 2014), lung cancer (Sapkota et al., 2008), high blood pressure (Baumgartner et al., 2011) and blindness (Pokhrel et al., 2005). People also assess their health more negatively when they use solid fuels for cooking (Liao et al., 2016; Liu et al., 2018a).

The objective of this paper is to complement this literature by focusing on the ability to cope with daily activities. We investigate the impacts of cooking fuel choice on this comprehensive measure of human health that goes beyond diagnosed diseases. Specifically, we analysed the extent to which the rural elderly was able to perform daily activities with greater ease if they cooked with non-solid fuels rather than solid fuels. We used data from a representative survey, the China Health and Retirement Longitudinal Study 2015, which covers about 450 villages in China. This study only focused on the rural population. Propensity score matching and endogenous switching regressions were used to address selection bias due to observed and unobserved confounds.

The novelty of our paper is twofold. First, while previous studies mainly focus on the impacts on children or middle-aged adults, we focused on the rural elderly in China who are particularly vulnerable to environmental pollution (Liu et al., 2018a). Since China is a rapidly aging society with a large rural population, our results may inform policymaking for this specific target population. Furthermore, due to environmental concerns such as deforestation, for many local governments energy transition in rural areas has become a topic of discussion, yet little is known about the possible health effects that such a transition may have. Second, we investigated people's body...
functionalities as health outcomes rather than doctors' visits, disease incidence or self-assessments. Although a reduction in body functionalities seems to be a matter of less concern, the associated economic losses due to decreased productivity could be considerable (Zivin and Neidell, 2018). Here we used the ability to cope with (instrumental) activities of daily living (ADL and IADL), two profound and reliable indicators, to capture body functionalities (Kalwij and Vermeulen, 2008). As comprehensive indicators, ADL and IADL not only cover physical and mental health status, but also represent the elderly people's capacity to live independently (Fillenbaum, 1985), which is a major public health concern for an aging society and will also have an impact on younger generations with respect to the costs of caring for the elderly (Tomiska et al., 2017). Furthermore, ADL and IADL are objective indicators and suffer less from measurement error than rough self-assessments (Ning et al., 2016). ADL and IADL have been widely used to assess the health impacts for the elderly on social security failure (Jensen and Richter, 2004), living arrangements (Weissman and Russell, 2016) and retirement (Nishimura et al., 2017).

The remainder of this paper is organised as follows. Section two provides an overview of the literature. In section three, we introduce the data and empirical strategy. In section four, we report the results, followed by a discussion of the results and conclusions in section five.

2. Literature review

Despite small variations across regions, the price of non-solid cooking fuels, such as natural gas and electricity, is controlled by the National Development and Reform Commission of China (Wang et al., 2009). The average price of non-solid cooking fuels is higher than that of solid cooking fuels. Biomass, which is the primary cooking fuel for the majority of rural households, is usually available for free in rural China. Although firewood markets exist, they are directed at productive and industrial purposes. Rural households collect biomass for cooking mainly from the wild and do not participate in market exchange. As in other countries, it is primarily women who are responsible for collecting biomass. As income increases, rural households often switch to non-solid fuels as their primary cooking fuels. A report shows that the population without access to clean cooking has fallen from 52% in 2002 to 33% in 2015 to 28% in 2018 (International Energy Agency, 2017; International Energy Agency, 2019).

A change in cooking fuel may reduce environmental pollution. For instance, incomplete combustion can lead to the emission of various harmful and hazardous materials into the air, such as particulate matter, polycyclic aromatic hydrocarbons, carbon monoxide, nitrogen oxides and sulfur dioxide (Li et al., 2011; Zhou et al., 2014; Liu et al., 2018b), among which the pollutants of PM2.5 or PM10 are particularly harmful to human health (Ezzati and Kammen, 2001; Baumgartner et al., 2011). Some studies (e.g. Sun et al. (2004), Rohde and Muller (2015) and Wang et al. (2017a)), have demonstrated the adverse effects of solid fuel use on general air quality and on indoor air quality in particular (Zhang and Smith, 2007; Li et al., 2011).

There is ample evidence on the adverse impact of indoor air pollution due to solid fuels on human health (Table A1). Epidemiological and environmental literature documents that, compared to solid-fuel stoves, clean-fuel stoves reduce the risk of cataracts (Pokhrel et al., 2005). There is also evidence that a household’s primary cooking fuel is related to the risk of neural tube defects, low birth weight and neonatal death in babies (Li et al., 2011; Epstein et al., 2013). Compared to wood and coal, non-solid fuels reduce the risk of various cancers (Sapkota et al., 2008) and improve people’s self-assessed health status (Liao et al., 2016; Liu et al., 2018a). Using an accurate measurement of indoor air pollution, e.g. PM2.5 or PM10, Ezzati and Kammen (2001) and Baumgartner et al. (2011) show that indoor air quality is correlated with respiratory infections and elevated blood pressure. There are also indications that the spread and mortality of the novel COVID-19 virus are negatively affected by pollution (Martelletti and Martelletti, 2020; Wu et al., 2020). However, except for Wylie et al. (2014), who employed propensity score matching (PSM), most of these studies pay insufficient attention to the endogeneity of cooking fuel choice.

Although some economic studies may also ignore the endogeneity concerns (Jagger and Shively, 2014), much of the economics literature is concerned with the identification of causal effects using advanced techniques or data generation. For example, a study using panel data found that the use of hazardous fuels increases the risk of respiratory illness in children (Gajate-Garrido, 2013). Some studies found that solid fuels increase the probability of respiratory infections and related health expenditure, using PSM to address selection bias (Yu, 2011; Rahut et al., 2017a; Qiu et al., 2019). Other empirical work employing instrumental variable approaches provided similar evidence on the negative effects of solid fuels (Edwards and Langpap, 2012; Silwal and McKay, 2015). Recently, studies have taken advantage of quasi-experimental (Imelda Imelda, 2018) or experimental (Barron and Torero, 2017) data to reveal the causal effect of a transition in cooking fuel choices on human health.

Despite vast empirical evidence of the effects of cooking fuel choice on human health, this literature is far from conclusive. Earlier research has focused on health outcomes such as doctors’ visits, disease incidence, self-assessed health conditions and health expenditure. Little is known about the health impacts of cooking fuel choice on people’s ability to cope with daily activities. Indeed, the various diseases caused by air pollution limit airflow and breathing, and even blood flow, and are characterised by respiratory symptoms. Consequently, patients may experience restrictions and discomfort in daily living (Skumlien et al., 2006). Here, we propose that the adoption of non-solid fuels for cooking may have a positive impact on body functionality more generally, which will also affect people’s ability to cope with day-to-day activities.

3. Data and empirical strategy

3.1. Data

This study used data from the China Health and Retirement Longitudinal Study (CHARLS) 2015 collected by Peking University. The focus here was on rural residents only. We believe that these data are of high quality and nationally representative of rural people aged 45 and above for two reasons. First, CHARLS used probability proportionate to size sampling, and the sample size was as large as 23,000 individuals from 450 villages or communities across China. Second, we compared the proportion of the rural sample to the proportion of the total Chinese rural population by age, and found that the figures were generally consistent. The CHARLS data collected a variety of variables, including demographic characteristics, family structure, housing characteristics and health status.

The aim of this paper was to link the concept of cooking fuel choice to individual health measures, namely the ability to cope with activities of daily living. The module on housing characteristics in the questionnaire asked about the main cooking fuel used by the household. People could choose from several options, including coal, natural gas, marsh gas, liquefied petroleum gas, electricity, crop residues, firewood and others (we excluded this category from the analysis). Our key explanatory variable was cooking fuel choice, and in line with Liu et al. (2018a) and Qiu et al. (2019) we grouped the observations into two categories: i) use of natural gas, marsh gas, liquefied petroleum gas and electricity (non-solid fuels), and ii) use of coal, crop residues and firewood (solid fuels).

The two measures of people’s ability to cope with daily activities are ADL and IADL. ADL refer to essential daily self-care activities (e.g. bathing, dressing, physical mobility, hygiene and eating), which do not require the use of instruments. IADL are activities related to independent living (e.g. housekeeping, cooking, using a phone, and...
3.2. Empirical strategy

3.2.1. Propensity score matching

A key difficulty in identifying causal effects of cooking fuel choice on health is the existence of confounders. People may choose different energy sources to maximise their utility, conditional on individual or household characteristics (Rahut et al., 2017b). Consequently, a simple comparison of health status between solid fuel users and non-solid fuel users would lead to biased estimates. We therefore employed propensity score matching (PSM), which resembles randomised assignment to treatment, to create conditions of a random experiment (Smith and Todd, 2005; Liu et al., 2018c) and eliminate the impact of covariates. The propensity score is the conditional probability of a person adopting non-solid fuels, calculated from a selection function of cooking fuel choices. Specifically, we defined the selection function as follows:

\[
FUEL_i = X_i \alpha + \epsilon_i \text{ with } FUEL_i = \begin{cases} 
1 & \text{if } FUEL_i > 0 \\
0 & \text{otherwise}
\end{cases}
\]  

(1)

where \(FUEL_i\) is a latent variable, indicating the utility of a person’s fuel choice. If the utility is positive, we observed that the person chooses non-solid fuels (\(FUEL_i = 1\)) for cooking; for a negative utility, we observed that the person chooses solid fuels (\(FUEL_i = 0\)). The exogenous variables \(X_i\) in the selection function determine the person’s utility, and \(\alpha\) is a vector of parameters to estimate, for instance by using a probit model. The predicted propensity scores from the selection function were then used to perform matching, according to commonly used matching algorithms, such as nearest neighbour, radius and kernel matching (Caliendo and Kopeinig, 2008).

Taking advantage of the large sample size, in nearestighbour matching, we selected one, five and ten matching partners respectively for each observation of non-solid fuels respondents (the treated) (indicated by NN = 1, 5, 10 in the tables below). We defined all matching within common support and set a caliper of 0.001 to reduce matching bias. After matching, the average treatment effect on the treated was defined as follows:

\[
ATT = E(Y_1|FUEL_i = 1) - E(Y_0|FUEL_i = 1)
\]  

(2)

where \(Y_1\) and \(Y_0\) are the health status of the matched non-solid and solid fuel users respectively.

Although PSM is commonly used in observational studies, its validity is subject to three assumptions: (1) a sufficient overlap of propensity scores between solid and non-solid fuel users before matching, (2) balancing in the covariates between solid and non-solid fuel users after matching, and (3) unconfoundedness, which means that in the selection function there is no omitted variable that is correlated with both \(FUEL_i\) and \(Y_i\). For assumption (3), which cannot be tested empirically, we reported the Rosenbaum bounds, which show how the results were robust to hidden bias due to potential omitted variables.

3.2.2. Endogenous switching regression model

Since PSM mitigates selection bias due to observables but not to unobservables, we tested the robustness of our results using an endogenous switching regression (ESR) that accounts for both observables and unobservables. ESR is suitable for studying “the impact of choice decisions allowing for endogeneity, sample selection and interaction between adoption and other covariates that affect the outcome equation” (Negash and Swinnen, 2013). ESR reports estimates of average treatment effects on the treated (ATT), which are comparable to that of PSM. The ESR model is defined in Eq. (1), which determines the regime a person faces, and two regression equations for the outcome variable under different regimes:

Regime 1: \(Y_{1i} = Z_i \beta_1 + \eta_1\) if \(FUEL_i = 1\)  
(3a)

Regime 2: \(Y_{0i} = Z_i \beta_0 + \eta_0\) if \(FUEL_i = 0\)  
(3b)

where \(Y_{1i}\) and \(Y_{0i}\) are measures of health status, which are only observed under regime 1 and 2 respectively. The vector \(Z_i\) consists of exogenous variables, which should not be identical to \(X_i\) and should exclude at least one instrumental variable in \(X_i\). The three error terms of \(\epsilon_1, \eta_1, \eta_0\) and \(\beta_1, \beta_0\) are assumed to have a trivariate normal distribution, with zero mean and constant variance. To correct potentially biased estimates of the parameters \(\beta_1, \beta_0\) due to omitted variables, the ESR model predicted the inverse Mills ratios \(\lambda_1\) and \(\lambda_0\) for solid and non-solid fuel users respectively from Eq. (1), and included them in the corresponding outcome equations:

Regime 1: \(Y_{1i} = Z_i \beta_1 + \lambda_1 \delta_1 + \eta_1\) if \(FUEL_i = 1\)  
(4a)

Regime 2: \(Y_{0i} = Z_i \beta_0 + \lambda_0 \delta_0 + \eta_0\) if \(FUEL_i = 0\)  
(4b)

where \(\delta_0\) and \(\delta_1\) are the parameters of the inverse Mills ratios. A full information maximum likelihood method was used to simultaneously estimate the selection and outcome equations (Lokshin and Sajaia, 2004). We used the parameter estimates to compute two expected outcomes: the expected health outcome of people who use non-solid fuels for cooking (see Eq. (5a)) and the expected health outcome of people in the counterfactual scenario, i.e. outcomes for those who use solid fuels (see Eq. (5b)):

\[
E(Y_{1i}|FUEL_i = 1) = Z_i \beta_1 + \lambda_1 \delta_1
\]  

(5a)

\[
E(Y_{0i}|FUEL_i = 1) = Z_i \beta_0 + \lambda_0 \delta_0
\]  

(5b)

The unbiased average treatment effect on the treated was derived as follows:

\[
ATT = E(Y_{1i}|FUEL_i = 1) - E(Y_{0i}|FUEL_i = 1)
\]  

(6)

Heterogeneity was investigated by restricting Eq. (6) to sub-groups for analysis.

3.2.3. Variable definitions

Table 1 displays variable definitions. The outcome variables are defined as the number of ADL or IADL for which the respondent does not need assistance. The key explanatory variable was non-solid fuel. In the survey, respondents were asked: “What is the primary cooking fuel in your family?”. The answer could be one of natural gas, marsh gas, liquefied petroleum gas, electricity, coal, crop residue or wood. We defined non-solid fuel as one if the answer was natural gas, marsh gas, liquefied petroleum gas or electricity, and zero if the answer was coal, crop residue or wood. In agreement with previous studies on the determinants of energy choice (Özcan et al., 2013; Behera et al., 2015; Rahut et al., 2016; Paudel et al., 2018), we included the respondents’ age, gender, education, marital status, employment status, smoking and drinking experience, household size, number of living children, total value of main durable assets and

\[\text{finance or medication management}\], which are more complex and require better health than ADL. For each activity, respondents were asked if they had difficulties performing the task independently. A total of 13 ADL and 5 IADL were used and respondents asked whether they could fulfil the task (see Table A2 for a description of these activities). Although the number of activities to measure ADL and IADL may appear small, they are often used in empirical work (e.g. Yeatts et al. (2013), Ning et al. (2016) and Che and Li (2018)).
The presence of heteroscedasticity of the residual in Eq. (7). We defined $Z'_i$ as STRUCTURE, because the Breusch-Pagan test reveals the largest value of Chi-square, indicating the strongest heteroscedasticity, when we regressed $FUEL$, on each of the control variables individually.

\[
FUEL_i = Z'_i \alpha_i + \epsilon_i
\]  

(7)

The validity of the generated instrumental variable required the presence of heteroscedasticity of the residual in Eq. (7). We defined $Z'_i$ as STRUCTURE, because the Breusch-Pagan test reveals the largest value of Chi-square, indicating the strongest heteroscedasticity, when we regressed $FUEL$, on each of the control variables individually.

Table 1

| Variables | Definitions |
|-----------|-------------|
| Health variables | |
| ADL | Number of activities of daily living for which assistance is not needed |
| IADL | Number of instrumental activities of daily living for which assistance is not needed |

| Cooking fuel choice | |
|---------------------|------------------|
| NON-SOLID FUEL | 1 = non-solid fuel for cooking; 0 = solid fuel for cooking |

Table 2 reports the summary statistics for the selected variables. With an average variance inflation factor of 1.23, we were not concerned about the presence of multicollinearity. Table 2 shows that there were statistically significant differences in respondents’ characteristics between solid fuel users and non-solid fuel users. Compared to solid fuel users, non-solid fuel users were on average younger, better educated, and had a greater probability of being married and having off-farm employment. They were also more likely to drink alcohol and have larger families, but fewer children. Their families also tended to be richer, but had less land. They also had a greater probability of living in houses with modern structures.

Table 2 also shows that compared to solid fuel users, non-solid fuel users are healthier on average in terms of their body functions (see our ADL and IADL measures). This may be interpreted as a first indication that a switch to non-solid fuel will improve people’s health. However, since other factors could impact both health and fuel choice, the selection effects needed to be addressed.

Table 3 reports the household-level determinants of cooking fuel choice.

Table 3 indicates that the elderly person’s family, where family members often need to be involved in collecting biomass (Rahut et al., 2017), we also included the female ratio in the selection function.

To rule out omitted variable bias, the ESR model requires that the instrumental variable should be strongly correlated with cooking fuel choice, but it should not affect health. We used the fraction of other surveyed individuals in the village who use non-solid fuels for cooking as an instrumental variable. Since the adoption of new technologies is often influenced by other people in the village (Minten and Barrett, 2008; Conley and Udry, 2010), the selected instrumental variable should be correlated with cooking fuel choice. Since the selection of cooking fuels by other households will have only minor impacts – if any – on the indoor air quality of a specific household, it should not affect the outcome variable. The use of other people’s average participation as an instrumental variable has been used in empirical work before (Liu et al., 2017; Liu et al., 2020).

We also employed a heteroscedasticity-based method to generate an additional instrumental variable (Lewbel, 2012). This method is useful when only one or no instrumental variable is available (Holland and Sene, 2016; Iosi and Lusardi, 2016). The generated instrumental variable is defined as, where $Z'_i$ is a subset variable of $Z_i$, and is the predicted residual of Eq. (7), which regresses $FUEL$, on $Z'_i$:

\[
FUEL_i = Z'_i \alpha_i + \epsilon_i
\]

(7)
and radius matching, the caliper was set at 0.001 to reduce potential matching bias. Notes: Matching is performed within common support. For nearest neighbour matching, the caliper was set at 0.001 to reduce potential matching bias. Authors’ computation.

The health effects of cooking fuel choice.

### Table 4

| Determinants of non-solid fuel choice. | Variables | Coefficients | Robust S.E. |
|--------------------------------------|-----------|--------------|------------|
| AGE                                  | -0.009*   | 0.002        |
| MALE                                 | -0.077b   | 0.030        |
| EDUJUNIOR                            | 0.149*    | 0.033        |
| EDUSENIOR                            | 0.169*    | 0.053        |
| MARRIED                              | -0.098a   | 0.038        |
| FARM                                 | -0.463a   | 0.025        |
| OFFFARM                              | 0.351*    | 0.031        |
| SMOKING                              | -0.050    | 0.072        |
| DRINKING                             | 0.019     | 0.029        |
| HHSIZE                               | 0.059*    | 0.011        |
| FRATIO                               | -0.037    | 0.068        |
| CHILDMNUM                            | -0.049a   | 0.009        |
| ASSETS                               | 0.013*    | 0.006        |
| STRUCTURE                            | 0.149*    | 0.025        |
| Constant                             | 0.304*    | 0.144        |
| Pseudo R²                            | 0.103     | Observations | 12,063    |

Notes: Authors’ computation. A standard t-test is performed to compare the mean difference between two groups.

* Significant at the 1% level; 

b Significant at the 5% level.

### 4.3. Results from propensity score matching

Table 4 reports the results of propensity score matching with three commonly used matching algorithms: nearest neighbour matching, radius matching and kernel matching. Compared to solid fuel users, non-solid fuel users were healthier in terms of body functionality. Differences in ADL and IADL between solid and non-solid fuel users were all statistically significant at the 1% level. The results were generally consistent across matching algorithms. Since the scales of the two health measures were different, we computed the relative difference in the health effects in proportions. The use of non-solid fuels for cooking increased respondents’ ADL by between 1.33% and 1.42%, and their ability to deal with IADL by between 3.02% and 3.40%. The greater effect on IADL may be explained by the greater effort it takes to perform them. Improvements in health would therefore show greater positive effects on IADL.

Given the positive health effects of non-solid fuel choice, one interesting question was whether the effects differed between population groups. Previous studies have demonstrated that there is socio-demographic heterogeneity in the health effects of air pollution exposure (He et al., 2016; Zhang et al., 2017). For example, He et al. (2016) found that children and extremely old people are more vulnerable to air pollution. In addition, because women are commonly in charge of cooking, they are also exposed more to indoor air pollution and may benefit more from the adoption of non-solid cooking fuels (Oluwole et al., 2012). Thus, we would expect that a switch to non-solid fuels has a greater positive effect on the older elderly and female elderly.

Specifically, we split the sample into two groups using an age threshold of 60 and analysed the health effects for each subgroup. Table 5 reports the results using different matching algorithms. The results showed that the use of non-solid fuels improved people’s ability to cope with IADL by at least 4.31% for those aged over 60. For people aged under 60 it ranged from 0.82% to 1.88%. We also ran the PSM models for men and women separately (Table 6). We found that women benefited more from the adoption of non-solid cooking fuels (Oluwole et al., 2012). Thus, we would expect that a switch to non-solid fuels has a greater positive effect on the older elderly and female elderly.

### Table 5

| The health effects of cooking fuel choice. | Matching algorithm | Variable | Absolute difference | S.E. | Relative difference | T-statistics | Rosenbaum bounds |
|------------------------------------------|--------------------|----------|---------------------|------|--------------------|-------------|------------------|
| NN (1)                                   | ADL                | 0.160    | 0.061               | 1.33* | 2.65*              | 2.888*      | 3.33-3.34        |
|                                           | IADL               | 0.135    | 0.029               | 3.02* | 4.60*              | 2.898*      | 3.33-3.34        |
| NN (5)                                   | ADL                | 0.170    | 0.051               | 1.41* | 3.33*              | 2.39-2.40   |                  |
|                                           | IADL               | 0.151    | 0.025               | 3.38* | 6.02*              | 2.56-2.57   |                  |
| NN (10)                                  | ADL                | 0.170    | 0.050               | 1.41* | 3.40*              | 2.59-2.59   |                  |
|                                           | IADL               | 0.145    | 0.024               | 3.25* | 5.92*              | 2.65-2.66   |                  |
| Radius                                   | ADL                | 0.170    | 0.049               | 1.42* | 3.45*              | 2.73-2.74   |                  |
|                                           | IADL               | 0.147    | 0.024               | 3.30* | 6.07*              | 2.73-2.74   |                  |
| Kernel                                   | ADL                | 0.167    | 0.049               | 1.39* | 3.38*              | 3.15-3.16   |                  |
|                                           | IADL               | 0.152    | 0.024               | 3.40* | 6.36*              | 3.33-3.34   |                  |

Notes: Matching is performed within common support. For nearest neighbour matching and radius matching, the caliper was set at 0.001 to reduce potential matching bias.

* Significant at the 1% level (T-statistics >2.58).
and from 0.82% to 1.88% for men. In general, the results offered some evidence that a switch to non-solid fuels has a relatively large positive effect on older people’s health. However, due to the overlap in the ranges of improvements for women and men, we were unable to confirm gender heterogeneity in health effects.

Tests of the three assumptions of PSM were performed. First, the overlap assumption posited that a sufficient overlap must exist between treated observations and matching partners for the estimated ATT to be valid for most or at least a sufficiently large proportion of observations. To test this assumption, we compared the kernel density distribution of the predicted propensity scores of solid and non-solid fuel users (Fig. A1). The range of propensity scores of solid and non-solid fuel users was almost identical, and only a few observations fell outside the range. Thus, the overlap assumption was well satisfied.

The second assumption was balancing in the covariates. The satisfactory estimation of this assumption eliminated the differences between covariates and ensured that the estimated ATT resulted from cooking fuel choice.3

4.4. Results from endogenous switching regression

We also applied ESR models (Table 7). The F-statistics from the joint test on the strength of the two instrumental variables in the selection function was 2237.94 (P-value <.001), implying that weak instruments were not a concern. Hansen-J statistics from the two-stage linear square estimation were 2.317 (P-value = .128) and 0.421 (P-value = .517) for ADL and IADL respectively, suggesting that the selected instruments do not substantially impact health status through channels other than cooking fuel choice.4

Compared to PSM, the ESR models generally showed greater effects of cooking fuel choice on ADL or IADL, which were all statistically significant at the 1% level. This underlines the need to use diverse empirical approaches to address selection bias due to unobserved confounds.

Notes: Authors’ computation.

3 There is no official test for the assumption of exclusion restriction of instruments in the ESR model. Results from the two-stage linear square (2SLS) are average treatment effects (ATE) rather than average treatment effects on the treated (ATT), although in our paper they are very similar. Since ESR does not concave for ADL, we dropped a few observations with zero value of ADL.

4...
Table 7
Average treatment effects on the treated from ESR model.

| Variable | Main effects | Age ≤60 | Age >60 | Female | Main effects | Age ≤60 | Age >60 | Female |
|----------|--------------|---------|---------|--------|--------------|---------|---------|--------|
| ADL      | 0.630        | 0.565   | 0.712   | 0.729  | 0.400        | 0.370   | 0.440   | 0.445  |
|          | 0.004        | 0.006   | 0.006   | 0.005  | 0.003        | 0.004   | 0.004   | 0.004  |
|          | 5.33%        | 4.63%   | 6.29%   | 6.30%  | 9.50%        | 8.24%   | 11.41%  | 8.02%  |
|          | 140.08**     | 103.16**| 113.87**| 136.65**| 134.12**     | 90.95** | 103.32**| 76.96***|

Notes: The T-statistics from the joint test on the strength of the two instrumental variables in the selection function is 2237.94 (P-value = .000). Hansen-J-statistics from two stage linear square estimation for ADL and IADL are 2.317 (P-value = .128) and 0.421 (P-value = .517), respectively. T-statistics from tests over the differences in the effects of cooking fuel choice on ADL are 11.6 (P-value = .000) for age and 16.4 (P-value = .000) for gender. T-statistics from tests over the differences in the effects of cooking fuel choice on ADL are 17.7 (P-value = .000) for age and 26.4 (P-value = .000) for gender.

* Significant at the 1% level.

Despite the different magnitude of the effects from ESR, the general pattern derived from the results of PSM was consistent across methods, i.e. the effects of non-solid cooking fuel choice were greater for IADL than for ADL. The results from ESR also showed that the effects of non-solid fuel choice were larger for women and older respondents. T-statistics from tests on heterogeneous effects between people aged over 60 and under 60 were 11.6 and 17.7 for IADL and ADL respectively. T-statistics from tests on heterogeneous effects between male and female elderly were 16.4 and 26.4 for IADL and ADL respectively. These results confirmed that the health effects of cooking fuel choice were heterogeneous for different sub-groups.

5. Discussion and conclusions

A large proportion of the rural population in the developing world still relies on traditional solid cooking fuels. The adverse effects of using such fuels have been well documented. This paper adds to this literature by investigating the determinants of cooking fuel choice and its health effects on body functionalities of the elderly, using data from the China Health and Retirement Longitudinal Study 2015. We estimated how cooking fuel choice was determined by several sociodemographic characteristics, such as age, gender, education and marital status. Off-farm work increased the probability of non-solid fuels being adopted. Household wealth and owning a modern house were also drivers of non-solid fuels being used. We also found that the use of non-solid fuels generated positive effects on a person’s ability to cope with activities of daily living (ADL), and even greater positive effects on a person’s ability to cope with instrumental activities of daily living (IADL). Specifically, the effects were as high as 5.35% for ADL and 9.50% for IADL.

Our results are not only in line with previous findings that the use of non-solid fuels reduces the risk of various diseases (c.f. Oluwole et al. (2012)), but also provide evidence of a new benefit of using non-solid fuels in terms of body functionalities. Since body functionalities are closely related to people’s life quality and productivity, our results highlight the need to support rural households’ energy transition to non-solid fuels. Moreover, the people to benefit most from progress in energy transition are the female elderly and older elderly, implying that energy transition can also contribute to greater intergenerational and gender equality.

Policy-wise, our results have important implications. As China turns into an aged society, the life quality of the elderly is becoming a major public policy concern. Our results imply that some of these concerns can be mitigated by policy instruments to encourage the use of non-solid fuels for cooking. For example, programmes providing subsidised loans to households to cover high upfront investment costs for the adoption of modern cooking equipment have proven successful in India (Nayak et al., 2015). Such subsidies or subsidised loans to rural households may also represent viable policy objectives for China. Furthermore, housing policy and labour market development may also encourage households’ use of non-solid fuels for cooking.

There are also some limitations in our study that should be addressed in future. In the survey, we only could access information on a household’s primary source of fuels, although households may use multiple sources of fuels simultaneously. Despite a focus on the primary source of fuels being in line with the energy ladder model, it may be an oversimplification of reality (Masera et al., 2000; Guta, 2012; Baijegunhi and Hassan, 2014). Other data sources with more detailed information should also be used in future. Furthermore, the impact of cooking fuel choice might be sensitive to whether the kitchen is separate from the living and sleeping areas, and whether the households were using improved stoves. Taking these into account may further distinguish the heterogeneous effects of cooking fuel choice and could have important implications for construction and stove regulations.

Acknowledgements

This work was supported by the Fundamental Research Funds for the Central Universities, National Natural Science Foundation of China [grant number 71673144 and 719101210], the Innovation Programme of the Shanghai Municipal Education Commission [grant number 2017-01-07-00-02-E00008] and the Natural Science Foundation of the Higher Education Institutions of Jiangsu Province [Grant number 17KJB170004].

Appendix A. Appendix

Table A1
Literature related to the impacts of cooking fuel choice on human health.

| Paper        | Area      | Dependent variable                        | Independent variable                        | Methods     | Main results                                      |
|--------------|-----------|-------------------------------------------|---------------------------------------------|-------------|--------------------------------------------------|
| Qiu et al.   | China     | Respiratory and cardiovascular diseases    | Solid fuels and non-solid fuels             | PSM         | Solid fuels increase the risk of respiratory and cardiovascular diseases |
| (2019)       |           | Chronic lung disease, heart disease and stroke, self-assessed health | Solid fuel, other fuels | Logistic regression | Solid fuels increase the risk of chronic lung diseases, chronic lung diseases, heart disease and reduce self-assessed health |
| Liu et al.   | China     | Infant mortality                          | Presence of fuel conversion programme       | DIDD        | Clean fuel programme reduces infant mortality    |
| (2018a)      |           |                                           | Clean fuel and dirty fuel                   | PSM         | Dirty fuel users have higher health expenditure  |
| Imelda Imelda| Indonesia | Health expenditures                       |                                              |             |                                                   |
| Rahut et al. | Bhutan    |                                           |                                              |             |                                                   |

(continued on next page)
Table A1 (continued)

| Paper                        | Area         | Dependent variable | Independent variable | Methods                        | Main results                                                                 |
|------------------------------|--------------|--------------------|----------------------|---------------------------------|--------------------------------------------------------------------------------|
| Barron and Tozeto (2017)     | El Salvador  | Respiratory infections | Treatments: with or without voucher for connecting to electricity grid | Fixed effect regression | Voucher reduces indoor air pollution and respiratory infection in children |
| Liao et al. (2016)           | China        | Self-assessed health and respiratory infection | Solid fuel-only users and other users | Descriptive statistics | Solid fuel users have lower levels of self-assessed health and a higher prevalence of respiratory diseases |
| Silwal and McKay (2015)      | Indonesia    | Lung capacity, reported cough or difficulty breathing | Firewood usage, other fuels usage (e.g., kerosene, liquefied petroleum gas, electricity) | IV-fixed effect regression, propensity score weighting | Firewood use reduces lung capacity, especially in women and children |
| Wylie et al. (2014)          | India        | Birth weight, preterm birth | Wood usage, gas usage | PSM, OLS and logistic regression | Wood usage has no effect on birth weight, but increases the risk of preterm birth |
| Jagger and Shively (2014)    | Uganda       | Respiratory infection | Biomass fuel consumption | Probit regression | More firewood use in non-forest areas increases the risk of respiratory infection; more crop residue use reduces the risk of respiratory infection |
| Gajate-Garrido et al. (2011) | Peru         | Respiratory illness in children | Non-hazardous cooking fuels (e.g., kerosene, gas or electricity) and hazardous cooking fuels | Fixed effect regression | The use of hazardous fuels increases the risk of respiratory illness in children, especially boys |
| Epstein et al. (2013)        | India        | Low birth weight, neonatal death | Primary fuel use | Multivariate regression | The use of coal, kerosene and biomass fuels causes low birth weight; the use of coal and kerosene increases the risk of neonatal death |
| Edwards and Langaap (2012)   | Guatemala    | Respiratory infection | Wood consumption | IV-Probit and 2SLS | More wood consumption increases the risk of respiratory infection |
| Li et al. (2011)             | China        | Neural tube defects | Coal or natural gas as primary cooking or heating fuels | Logistic regression | Coal usage increases the risk of neural tube defects in children |
| Baumgartner et al. (2011)    | China        | Elevated blood pressure in women | PM$_{2.5}$ exposure from biomass combustion | Mixed-effect model | Exposure to PM$_{2.5}$ increases the risk of elevated blood pressure |
| Yu (2011)                    | China        | Respiratory infections | Treatment with or without improved stoves | PSM, DID | Improved stoves reduce respiratory infections |
| Sapkota et al. (2008)        | India        | Cancers | Modern fuel usage, coal and wood usage | Logistic regression | Long-term coal and wood usage increase the risk of cancer |
| Pokhrel et al. (2005)        | Nepal and India | Cataract | Clean-burning stove, fluided and unfuild solid-fuel stove | Logistic regression | Clean-burning stove reduces the risk of cataracts |
| Ezzati and Kammen (2001)     | Kenya        | Respiratory infections | PM$_{2.5}$ exposure from biomass combustion | Fixed effects model | Respiratory infections are increasing concave functions of daily exposure to PM$_{10}$ |

Sources: Authors’ collection.

Table A2
Questions for the measures of ADL and IADL.

| Variables | Questions |
|-----------|-----------|
| ADL       | Do you have difficulty walking 100 m? Do you have difficulty getting up from a chair after sitting for a long period? Do you have difficulty climbing several flights of stairs without resting? Do you have difficulty stooping, kneeling or crouching? Do you have difficulty reaching or extending your arms above shoulder level? Do you have difficulty lifting or carrying weights over 5 kg, like a heavy bag of groceries? Do you have difficulty picking up a small coin from a table? Because of health and memory problems, do you have any difficulty dressing? Because of health and memory problems, do you have any difficulty bathing or showering? Because of health and memory problems, do you have any difficulty eating, such as cutting up your food? Do you have any difficulty getting into or out of bed? Because of health and memory problems, do you have any difficulties with using the toilet, including on and off? Because of health and memory problems, do you have any difficulties controlling urination and defecation? |
| IADL      | Because of health and memory problems, do you have any difficulties doing household chores? Because of health and memory problems, do you have any difficulties preparing hot meals? Because of health and memory problems, do you have any difficulties shopping for groceries? Because of health and memory problems, do you have any difficulties managing your money, such as paying your bills, keeping track of expenses, or managing assets? Because of health and memory problems, do you have any difficulties making phone calls? |

Notes: For each question, the possible answers are (1) No, I don’t have any difficulty; (2) I have difficulty, but can still do it; (3) Yes, I have difficulty and need help; (4) I cannot do it.

Table A3
Matching quality.

| Variable | Before matching | After matching |
|----------|----------------|---------------|
|          | Treated | Control | T-statistics | Treated | Control | T-statistics |
| AGE      | 59.78   | 62.53   | −15.54$^a$ | 60.10    | 59.94   | 0.91         |
| MALE     | 0.47    | 0.47    | 0.38        | 0.47     | 0.47    | −0.89        |
| EDUJUNIOR| 0.23    | 0.16    | 10.00$^a$  | 0.22     | 0.23    | −1.16        |
| EDUSENOR | 0.08    | 0.05    | 6.74$^a$   | 0.07     | 0.07    | −0.27        |
| MARRIED  | 0.87    | 0.85    | 3.40$^a$   | 0.87     | 0.87    | −0.17        |

$^a$ Significance level at the 5% level.
Table A3 (continued)

| Variable | Before matching | After matching |
|----------|-----------------|----------------|
|          | Treated | Control | T-statistics | Treated | Control | T-statistics |
| FARM     | 0.50    | 0.67    | −19.35$^a$ | 0.52    | 0.52    | −0.62 |
| OFFFARM  | 0.33    | 0.16    | 21.28$^a$  | 0.31    | 0.32    | −1.51 |
| SMOKING  | 0.97    | 0.57    | 0.48       | 0.97    | 0.97    | 0.16  |
| DRINKING | 0.35    | 0.33    | 1.95$^b$   | 0.34    | 0.34    | 0.54  |
| HHsize   | 2.67    | 2.47    | 9.26$^a$   | 2.64    | 2.65    | −0.21 |
| FRATIO   | 0.51    | 0.51    | −0.55      | 0.51    | 0.50    | 1.01  |
| CHILDNUM | 2.59    | 2.94    | −13.09$^a$ | 2.62    | 2.62    | 0.09  |
| ASSETS   | 2.65    | 0.71    | 8.54$^a$   | 1.23    | 1.26    | −0.49 |
| STRUCTURE| 0.90    | 0.72    | 27.00$^a$  | 0.90    | 0.89    | 1.43  |

Notes: Matching quality is from nearest neighbour matching with ten partners. Matching quality with other algorithm produces close results.
Before matching: Pseudo $R^2 = 0.103$, LR Chi$^2 = 1717.5$ ($P$-value = .000), mean bias = 16.3%.
After matching: Pseudo $R^2 = 0.001$, LR Chi$^2 = 8.85$ ($P$-value = .841), mean bias = 1.1%.
$^a$ Significant at the 1% level; $^b$ Significant at the 10% level.

Fig. A1. Distribution of propensity scores.

Appendix B. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2020.104811.

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