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Household appliance ownership and income inequality: Evidence from micro data in China

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ABSTRACT

As the residential sector is becoming increasingly important in the total energy consumption and appliance ownership is a significant but under-examined driver, this study investigates the relationship between income inequality and appliance ownership using panel data from the China Health and Nutrition Survey (CHNS). We find that income inequality has negative impacts on appliance penetration rate across specifications, except for the initial development stage. On average, households start adopting air conditioners at a threshold of over 60,000 (2011 RMB) based on annual income, much higher than TV, fridge and washer (8500–9000 RMB). The empirical results validate the S-shape curve of appliance established in the literature. To understand the magnitude of the impact and policy implications, we further simulate the impact of poverty alleviation and the penetration paths under inclusive versus exclusive income growth. Our results demonstrate that current poverty line is too low to achieve appliance adoption – a signal for modern life-styles. In addition, a more inclusive growth path could lead to much higher penetration for regions that have relatively low growth rate.

1. Introduction

China has experienced booming energy consumption growth over the years, with the soaring economy as well as acceleration of industrialization and urbanization. It not only represents a great proportion of the world energy consumption, but also remains to be the driving force of the energy consumption growth in the coming decades. From 2000 to 2016, the total final energy consumption of China has more than doubled, from 781,194 ktoe (1000 tons of oil equivalent) to 1,969,366 ktoe, at an average annual growth rate of 6% (International Energy Agency, 2019). With the rapid growth, the energy consumption of China surpassed that of the United States in 2019, where the total final energy consumption fluctuated around 1,500,000 ktoe. By contrast, the total final energy consumption across the world grows at 2%. There is no doubt that China is a main driving force of world's energy growth.

Along with the economic boom and the growing purchase power of the households, the energy consumption in the residential sector has become the second largest energy-consuming sector after the industrial sector. It grows steadily from 14% in 2010 to 16% in 2016 of China's total final energy consumption (International Energy Agency, 2019). In comparison, under Chinese government's policy to encourage energy saving and control emission in the 11th and 12th Five-year Plans (Zhou & Teng, 2013), industrial energy consumption has shown a declining trend in recent years, making residential sector a more important component of energy consumption. The share of the industrial sector energy consumption in China's total energy consumption has decreased from 54% in 2011 to 50% in 2016. This trend emphasizes the importance to put more attention on the residential energy consumption. Furthermore, it is expected that China's residential energy consumption will have large potential to grow. As to the residential energy

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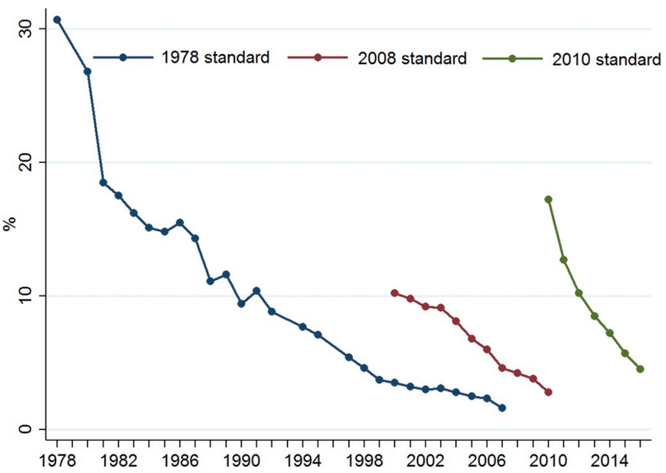

Fig. 1. Rural poverty rate (1978–2016).

consumption per capita, in 2016 OECD country's residential energy consumption is 0.53 tons of oil equivalent of energy while for China it is 0.24, nearly half of that of OECD country (International Energy Agency, 2019). If we expect Chinese households to catch up with their western counterparts, this gap points to great growth potential. Therefore, understanding the factors influencing residential energy consumption in China is essential for predicting China's energy consumption.

Among the components of residential energy consumption, electricity consumption has more than quadrupled, rising from 12,485 toe to 72,404 toe during 2000–2016, rising exceedingly faster than and becoming a larger portion in the total residential energy consumption, with rapid shrinking of biofuels and waste (International Energy Agency, 2019). This indicates an ongoing structural shift of residential energy consumption from biofuels and waste to electricity. It has been pointed out that household electricity demand growth is driven by household electric appliances increasingly (Ürge-Vorsatz et al., 2012). Meanwhile, the adoption of electric appliances by consumers, especially in urban areas of China, has been astonishing. Thus, learning more about electric appliance will contribute to a more precise prospective of future energy growth in China.

Previous studies have examined an S-shaped relationship between energy-using assets and household income. Based on S-shape, the adoption of appliances only increases after income reaches a certain threshold, below which the income elasticity is very low. The household-level S-shaped relationship has implication for aggregated energy consumption, which is critical for estimation and forecast of total energy demand in the residential sector. If we consider two communities with the same level of average income, the community with extreme income inequality would have lower appliance ownership in total based on the theoretical prediction of S-shape, compared with the community with more even income distribution. As pointed out in Cao, Ho, Li, Newell, and Pizer (2017), most widely used estimation and prediction model use aggregated data that are usually available at provincial level or even country level. Almost all of them neglect the income distribution. Auffhammer and Wolfram (2014) shows that the impact of inequality is overall negative, however, it does not illustrate how significant the magnitude is, which makes it difficult to judge whether we should consider the inequality factor in modeling. The panel data at provincial level also limit the total number of observations for analysis, which is improved in our case through using the community level data instead. We examine appliance ownership instead of the direct electricity consumption because electricity consumption is usually not reported in surveys. Even when reported, the number could be less reliable than appliance ownership, which is very straightforward to count. The downside of using appliance ownership is that the usage pattern and technology efficiency could vary when the count of appliance is the same. Nonetheless, accurate understanding of appliance ownership is itself meaningful to energy demand estimation and forecast.

The inequality factor, which is often neglected in energy modeling, has its own significance under the current development stage and policy context in China. According to the 13th Five-Year Plan (2016–2020) released by the China's State Council, China aims to eradicate rural poverty by 2020, ensuring adequate food, clothes, education, health services and housing. Since the reform and opening up policy in 1978, China experienced massive economic growth and gradually established itself as one of the leading economies in the world. Meanwhile, by implementing various and evolving anti-poverty policies, China plays a key role in global poverty reduction efforts, demonstrated by the decreasing rural poverty rate in Fig. 1.[1] From 2013 to 2016, the rural population in poverty under 2010 rural poverty standard (2300 RMB) reduced roughly 14 million per year, which is equivalent to twice the population in Hong Kong. Per capita disposable income for rural population in poor regions increased at the growth rate of 10.7% per year on average, exceeding the national average of roughly 6%.[2] In 2016, < 5% rural residents live in poverty.

[1] These data are from http://www.stats.gov.cn/tjsj/ndsj/2017/indexch.htm (accessed July 21, 2018).

[2] Data regarding the progress on poverty alleviation are from the website of National Bureau of Statistics http://www.stats.gov.cn/tjsj/ndsj/2017/indexch.htm (accessed July 21, 2018) and the Report of the State Council on the work of poverty alleviation and hard work, reported on the twenty-ninth meeting of the Standing Committee of the Twelfth National People's Congress in August 29, 2017. See http://www.npc.gov.cn/npc/xinwen/2017-08/29/content_2027584.htm (accessed July 9, 2018).

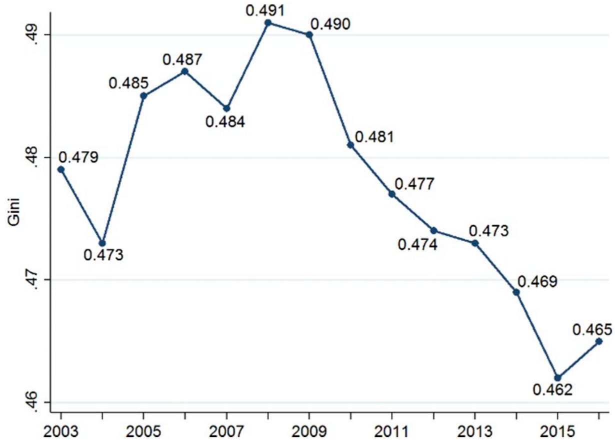

Fig. 2. Gini Index (2003–2015).

However, if we look at the whole income distribution (not just the bottom), the rapid economic growth was accompanied by rising income inequality (Xie & Zhou, 2014). Based on the Gini index released by the National Bureau of Statistics (NBS), the inequality increased until 2008 and then decreased from 2008 to 2015 (Fig. 2). Though the exact estimation of income inequality is still in debate (Li & Luo, 2011; Yue & Li, 2013), most scholars agree that income inequality in China has reached a high level, with Gini index larger than that of the United States (Xie, Zhang, Xu, & Zhang, 2013). Some studies – using different sources of data – report Gini indexes ranging from 0.483 to an alarming level of 0.61 (Gan, 2013; Li & Luo, 2011; Xie & Zhou, 2014), significantly larger than the numbers reported by NBS.[3]

At the macro level, previous literature have established that inequality hinders human capital accumulation and skills development, undermines education opportunities, lowers social mobility, increases social conflicts (e.g. Alesina & Perotti, 1996) and violent crime levels (e.g. Hsieh & Pugh, 1993), thus ultimately leading to lower economic growth (e.g. Aghion, Caroli, & Garcia-Penalosa, 1999; Cingano, 2014). At the micro level, there has been evidence showing that increase in income inequality contributes to the rise in household economic distress (Boushey & Weller, 2008), compared to the inverted-U relationship between inequality and individual happiness (Wang, Pan, & Luo, 2015), as well as between inequality and health (Li & Zhu, 2008). Keeley (2015), in the book *Income Inequality*, examines the trend in income inequality and its boarder consequences.

In addition to the implications to the energy modeling and forecast, this paper also contributes to the general understanding of inequality impact by using appliance penetration rate as a proxy to modern living standards. For urban households living in developed regions such as Beijing and Shanghai, it is almost impossible to imagine living without TV, washer, fridge and air conditioner (AC). These electric appliances provide basic services to modern households, including cooking, entertaining, heating, cooling and cleaning (Day, Walker, & Simcock, 2016; Fell, 2017). As stated by Hunt and Ryan (2015), 'Energy practitioners often emphasize that energy is desired not for its own sake, but for the services that it produces'.

More specifically, we use panel data at the community level, from the China Health and Nutrition Survey (CHNS), to estimate the impact of inequality on appliance penetration rates for TV, fridge, washer and AC. Expanded on the Auffhammer and Wolfram (2014), we find that inequality has a negative impact on penetration rates. This relationship holds for most specifications and for most parts in the income distribution. Only for communities at the initial development stage, inequality is shown to have positive effects. These findings are consistent with the S-shape relationship established in the literature (Auffhammer & Wolfram, 2014; Farrell, 1954; Gertler, Shelef, & Wolfram, 2016). By using a wide range of percentiles in calculating the share of population under the income cutoff, we are able to identify income thresholds for appliances adoption: 8500–9000 RMB for TV, fridge and washer and > 60,000 RMB for AC, based on annual household disposable income (in 2011 RMB).

To understand the magnitudes of the impact, we simulate (i) the effect of poverty alleviation policies and (ii) inclusive versus exclusive growth paths. It is worthwhile to note in advance that both simulations are based on strong assumptions and should be interpreted with caution. With relatively low poverty lines (< 3000 RMB, roughly $500 per year), poverty alleviation is shown to have limited impacts on the penetration rates. This suggests that, absent subsidies for appliance adoption, higher poverty lines have to be set, if the poor are expected to catch up in terms of using electricity in daily life.

Given the high growth rate in China, change in income distribution is shown to have negligible effects on penetration rate. This has to be interpreted carefully, as the effect of inequality could be much more substantial for regions and countries with lower income growth rates. This has important implications for the least developed regions in China, as well as less developed countries in the world. For example, in Brazil, which is relatively wealthy but unequal, the government actively pursued policies aimed at reducing

[3] Note that many researchers hold a cautious attitude towards the Gini index from NBS. It is criticized for lack of open access to the original micro-level data to confirm the Gini index released (Xie & Zhou, 2014). However, it also has the advantage of sample size and sampling method compared to other sources of household survey. The accuracy of Gini index is beyond the scope of this paper.

poverty and promoting social equality (Pereira, Freitas, & da Silva, 2011). Our results suggest that a more inclusive growth[4] path could promote appliance adoptions, which implies that a model that neglects income distribution might underestimate the future penetration rate.

The rest of the paper is organized as follows. Section 2 describes the data, highlights the trends in inequality and appliance penetration and confirms the representativeness of our sample. Section 3 introduces the diffusion model and sets foundation for econometric analyses. Section 4 summarizes the empirical results and Section 5 concludes and discusses the limitations and future steps.

2. Data

2.1. Data source

Our data comes from the China Health and Nutrition Survey (CHNS)[5] – one of the most widely used surveys for micro-level research in China. The survey is conducted by China Center for Disease Control and Prevention and Carolina Population Center, the University of North Carolina at Chapel Hill, and designed as a time-cohort survey. Employing a multi-stage, random cluster design to draw a sample of households, the CHNS covers both rural and urban households of 15 Chinese provinces and municipal cities[6] that vary substantially in socio-economic indicators (see Appendix Fig. S1. for the map). Up to now, ten waves of CHNS data have been collected (for the years 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, 2015). As 2015 files are only partially available recently, we use data until 2011. Given that the three provinces Zhejiang, Shaanxi and Yunnan have not participated in the household survey during 1989–2011, we exclude them in our study.

The CHNS originally surveyed 3795 households and 15,907 individuals, and later rounds added all new households formed from original ones. The survey contains detailed information about household income, dwelling features, appliances owned by the household, electricity usage at household level and related features of members of the household. Following Auffhammer and Wolfram (2014), this study focuses on the analysis of four main household appliances: TV, fridge, washing machine and air conditioner (AC), which are the most common appliances in the Chinese households.

To study the inequality and appliance penetration rate at the community level,[7] we average the household variables to produce variables at community level for empirical analysis (except for the inequality variables, which were constructed as below). For instance, we average the dummy variable indicating whether the household in a community owns a certain type of appliance to get the penetration rate for that community. Our final sample covers 1920 observations at the community level with at least 188 observations in each survey year.

2.2. Descriptive analysis

2.2.1. Appliances ownership

The solid lines in Fig. 3 represent the trend of average number of appliance owned per 100 households in our dataset.[8] The number of appliance owned by every 100 households has been increasing rapidly since 1990s for all appliances. TV is the most widely owned appliance, reaching 139.76 every 100 households on average in 2011. This is in line with previous studies in the literature indicating TVs are the first and most widely acquired appliance (Rao & Ummel, 2017). Washer and fridge are also widely owned, with number of 85.40 and 84.01 every 100 households respectively in 2011. On the whole, air conditioner (AC) is the least prevailing, but increased rapidly from 30.19 in 2006 to 86.32 in 2011.

To confirm the representativeness of our data, the same indicator provided by NBS is presented in the same graph with dash line.[9] The two results manifest high level of consistency with each other for TV, washer and fridge, with similar trend and close proximity of value. This indicates that the sample we use is well representative of the whole China in the ownership of the three appliances. For AC, our sample demonstrates downward bias for some years but without systematic offset. Overall, our sample is confirmed to be representative of China in terms of appliance ownership.

[4] We use 'inclusive' to mean development paths that bring more even income distributions – less inequality.

[5] See http://www.cpc.unc.edu/projects/china. This research uses data from China Health and Nutrition Survey (CHNS). We thank the National Institute of Nutrition and Food Safety, China Center for Disease Control and Prevention, Carolina Population Center, the University of North Carolina at Chapel Hill, the NIH (R01-HD30880, DK056350, and R01-HD38700) and the Fogarty International Center, NIH for financial support for the CHNS data collection and analysis files from 1989 to 2006 and both parties plus the China-Japan Friendship Hospital, Ministry of Health for support for CHNS 2009 and future surveys.

[6] The 12 provinces are Liaoning, Heilongjiang, Jiangsu, Zhejiang, Shandong, Shaanxi, Henan, Hubei, Hunan, Guangxi, Guizhou, Yunnan. The 3 municipal cities are Beijing, Shanghai and Chongqing.

[7] We use "community" to refer to village in this paper.

[8] To prove the representativeness of our dataset, we use average number of appliance owned by every 100 households instead of ownership rate to display the trend of appliance ownership, since only this indicator is available by NBS. In our dataset, there is one variable indicating the number of appliances owned by the household. We average this variable and multiply it by 100 to generate this indicator.

[9] Note that before 2013, NBS separated the statistical data of rural and urban. Thus we use rural population and urban population in the corresponding year to produce weighted average as this indicator for rural and urban combined.

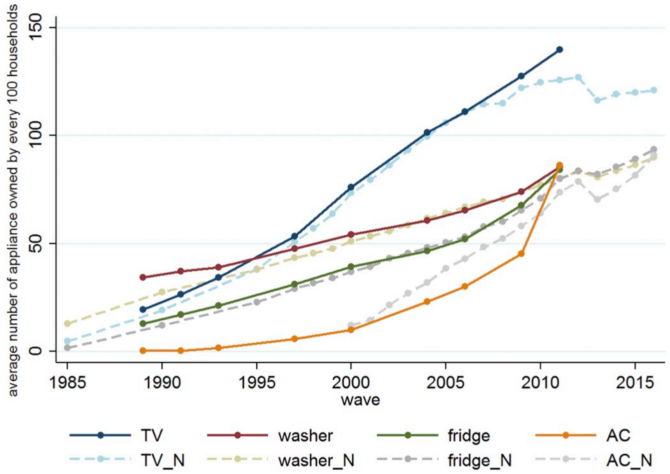

Fig. 3. Average number of appliance owned by every 100 households.
Notes: The variables with suffix "_N" are from NBS while those without are from our dataset.

2.2.2. Income inequality index

In order to analyze the effect of income distribution on appliance ownership, we construct two measures to describe the income inequality levels in different communities. Generally speaking, Gini index is usually used when considering income inequality issues. For instance, Yu and Xiang (2014) used the micro-level data to calculate Gini index to depict the inequality in China. However, given the fact that the sample size in each province is relatively small, our data set is not well suited to calculating the Gini index for different provinces. We therefore decide to create our own indexes.

Constructing a proper index is not unusual in previous studies. For instance, Auffhammer and Wolfram (2014) used the proportion of households whose annual incomes are lower than 3000 RMB in each province to reflect income distribution. We also use similar measures in our analysis (directly introduced in the results section because the definition is straightforward). The problem with this kind of proportion definition is that the measure only varies if households' income passes the cutoff that is chosen subjectively (e.g. 3000 RMB). Put it in another way, if income of households under the cutoff grow to only slightly under the cutoff, the measure would not count this change as improvements in income distribution, let alone any income growth for lower middle-income households. Furthermore, the results could be very sensitive to the choices of cutoffs. Indeed, as our results show, coefficients vary with the cutoffs.

To mitigate these problems, our inequality indexes are based on standard deviations. Essentially, the indexes are relative standard deviations, i.e. standard deviation over the mean. More specifically, the first inequality measure is calculated as below:

$$inequality_{j,t} = \frac{\sqrt{\frac{1}{N_{j,t}}\sum_{i=1}^{N_{j,t}}(income_{i,j,t} - \mu_{j,t})^2}}{\mu_{j,t}} \tag{1}$$

$inequality_{j,\,t}$ is the income inequality index for community j in year t. $income_{i,\,j,\,t}$ is the income of household i in community j in year t. $\mu_{j,\,t}$ is the average household income in community j in year t. $N_{j,\,t}$ is the sample size in community j in year t.

The second measure for inequality only involves the low-income households and essentially measures the income inequality of households whose income is below the average income in the community. It is calculated as below:

$$inequality\_b_{j,t} = \frac{\sqrt{\frac{1}{N\_low_{j,t}}\sum_{i=1}^{N\_low_{j,t}}(income\_low_{i,j,t} - \mu\_low_{j,t})^2}}{\mu\_low_{j,t}} \tag{2}$$

The notations are similar as above. The only difference is that only households below the average income enter into this calculation, thus highlighting the income distribution changes among the lower income households. If, for example, the rich grows much richer, our first inequality measure will increase, while the second stays the same.

The two measures of inequality are illustrated in Fig. 4 with box plots. Within each year, inequality measures vary for communities. The boxes represent the 25st and 75th percentiles of inequality for communities in a given year, showing considerable variations. This is important in identifying the effect of inequality, as we control for year indicators to rule out structural changes from year to year that would lead to changes in appliance adoption. Over time, both inequality measures increase until 2009 and slightly decrease in 2011, indicating that the income gap widened from 1990s to early 2000s. This trend consists with the Gini index from NBS and other literatures. Overall, the Gini index of China increased from 1995 to 2009, according to NBS (see Appendix Fig. S2

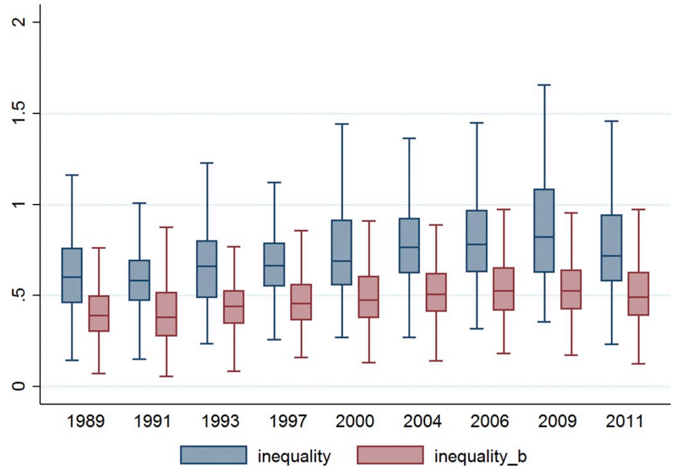

Fig. 4. Income inequality at the community level by year.
Notes: The bottom and top end of the blue or red bars show 1% and 99% of the inequality distribution for all communities in a given year.

for the Gini index from 1995 to 2016). After 2009, the Gini index experienced a sharp decrease and continued to decline until 2015.[10] The consistency implies that the index we construct is reasonable and can well demonstrate the level of income inequality.

2.2.3. Socio-demographic and economic characteristics

We also include other control variables in our empirical analysis. According to the literature, education level, dwelling features, household composition, race, employment status, among other factors, affect the appliance ownership (Leahy & Lyons, 2010; Matsumoto, 2016; O'Doherty, Lyons, & Tol, 2008; Rao & Ummel, 2017; Rong & Yao, 2003). Electricity access is also an important variable affecting appliance penetration rate (Auffhammer, 2014; Rong & Yao, 2003). Therefore, we have controlled variables such as household income (in 2011 RMB), educational level of household heads and other relevant variables. As mentioned before, we construct corresponding community-level variables based on the averages of household data. The descriptive statistics of the community-level variables are summarized in Table 1.

As can be seen from Table 1, the average community-level income is 24,261 RMB, with a standard deviation of 17,332 RMB, indicating that income vary substantially across different communities and over years. We also compare per capita income deduced from our dataset and from data provided by NBS[11] to examine the representativeness of our sample in income. Overall, the two measures show similar pattern in trend and value (see Appendix Fig. S3 for the comparison). However, note that after 2000, the two measures depict widening differences, with the per capita income derived from our dataset lower than that from NBS by 1252 RMB in 2004 to 2703 RMB in 2011. This indicates slight downward bias of our sample in income after 2000, maybe due to the rapid economic change in the other regions of China.

With rural electrification programs, electricity access in China has dramatically improved, leading to 12.2% decrease in the average days of power failure per week. Over the whole sample periods, however, communities experience blackouts for half day each week. For communities without reliable electricity, the service flows from the appliances are not guaranteed, resulting in less adoption. Among other variables, educational level of the household head and household dwelling size also increased. Household size shrinks slightly probably owning to the birth control policy.

3. Method

We adopt the diffusion model to analyze the relationship between income distribution and appliance ownership. Diffusion model has been widely used in previous studies. The general form of the diffusion relationship follows an S-shaped function (McNeil & Letschert, 2010). Among the various options for modeling this type of relationship, it is common to use a logistic model in the literature (Auffhammer, 2014). McNeil and Letschert (2010) employed this model to study the diffusion of electrical appliances in the residential sector. They developed a cross-sectional version of this model, specified as below:

$$Diff_i = \frac{\alpha_i}{1 + \gamma \exp(X_i \beta)} \tag{3}$$

[10] Gini index of China is from the website of NBS http://www.stats.gov.cn/tjzs/tjsj/tjcb/zggqgl/200210/P020130912449774383370.htm and http://www.stats.gov.cn/ztjc/zdtjgz/yblh/zysj/201710/t20171010_1540710.html (accessed July 22, 2018). The detailed information about Gini index during this period is present in the Appendix.

[11] We use the household income and household size to generate per capita income for each year in our dataset. And we produce per capita income with income per capita for village and urban and corresponding population in the data of NBS.

Table 1
Descriptive statistics of variables, 1989–2011.

	Variable	Mean	sd	Min	Max	%change
Penetration rate of TV	*vill_TV*	0.660	0.368	0	1	3.6%
Penetration rate of washer	*vill_washer*	0.558	0.332	0	1	2.2%
Penetration rate of fridge	*vill_fridge*	0.427	0.361	0	1	3.1%
Penetration rate of AC	*vill_AC*	0.164	0.288	0	1	2.1%
Income features						
Income	*vill_income*	24,261	17,332	774	123,474	6.1%
Income inequality	*inequality*	0.759	0.316	0.146	3.401	0.9%
Income inequality within the low-income group	*inequality_b*	0.490	0.183	0.057	1.452	1.3%
Education of household head						
Percentage of household heads with middle school or equivalent education	*vill_edu_m*	0.295	0.148	0	0.882	0.3%
Percentage of household heads with high school or equivalent education	*vill_edu_h*	0.176	0.151	0	1	0.4%
Percentage of household heads with college level or above education	*vill_edu_c*	0.054	0.122	0	0.8	0.3%
Demographic features						
Average dwelling size	*vill_dwsize*	108.721	63.020	9	760	2.9%
Average household size	*vill_hhsize*	3.600	0.793	1.5	6.143	−1.2%
Percentage of household heads who are married	*vill_married*	0.859	0.117	0.333	1	−0.4%
Percentage of household heads who are minority	*vill_minority*	0.132	0.269	0	1	−0.5%
Percentage of household heads who work in state-owned enterprises	*vill_work_soe*	0.230	0.284	0	1	−1.3%
Percentage of household heads who work in collective enterprises	*vill_work_collective*	0.268	0.355	0	1	−1.8%
Location of the community (=1 if rural)	*rural*	0.657	0.475	0	1	−0.3%
Electricity access						
Average days of power failure per week	*vill_daysbreak*	0.518	1.287	0	7	−12.2%

Note: For continuous variables, the "%change" is calculated as the average annual growth rate for 1989–2011. For variables indicating percentage, the "%change" is calculated as the mean annual change for 1989–2011.

where $Diff_i$ is the penetration rate of an appliance in province i, α_i is the saturation level of the appliance for province i, always chosen according to the maximum observed diffusion levels of high-income countries. X_i is the vector of explanatory variables of province i. This model can be rearranged as:

$$\ln\left(\frac{\alpha_i}{Diff_i} - 1\right) = \ln\gamma + X_i\beta + \varepsilon_i \tag{4}$$

Auffhammer (2014) developed a panel-data version to analysis the impact of income and short run weather on AC adoption, where they controlled for province and year fixed effects and restricted α_i to be identical for each province. Auffhammer and Wolfram (2014) employed a similar model to study the impact of income inequality on household appliances penetration rate:

$$\ln\left(\frac{\alpha}{Diff_{it}} - 1\right) = X_{it}\beta + \varepsilon_{it} \tag{5}$$

where ε_{it} is an error term, which contains either province ($\varepsilon_{it} = \gamma_i + \eta_{it}$) or year ($\varepsilon_{it} = \phi_t + \iota_{it}$) specific fixed effects.

Accounting for the longitudinal data that we use, our estimation equation follows Auffhammer (2014) and Auffhammer and Wolfram (2014) and is specified as below:

$$\ln\left(\frac{\alpha}{Diff_{it}} - 1\right) = \beta_0 + \beta_1 inequality_{it} + \delta X_{it} + province_i + year_t + \varepsilon_{it} \tag{6}$$

where $Diff_{it}$ is the penetration rate of an appliance in community i, X_i is the demographic and social-economic variables. We set $\alpha = 1$ given that the maximum penetration rate is 1. We consider the behaviors regarding owning appliances, but not how many appliances the households decide to own.

Practically, we modify the model since the appliance penetration rate in a community may be 0 or 1. The dependent variable is changed to $\ln\left(\frac{1.011}{Diff_{it} + 0.001} - 1\right)$. This modification would not change the structure of the model and it can assure the best use of the data by preventing the occurrence of missing values when dividing or taking logs. In addition, when we run regressions, we use the negative numbers to make the coefficients easier to interpret. For example, the coefficient before income in original diffusion model would be negative based on model (Cao et al., 2017), actually reflecting a positive effect of income on appliance penetration (because diffusion is in denominator). After taking the opposite of the left-hand side before regressing, the reported coefficients are positive for income and negative for inequality, and 'positive sign' would conveniently suggests positive impact on diffusion.

4. Empirical results

In this paper, we test the hypothesis that income inequality has a negative impact on appliance adoption. As incorporating a

Table 2
Five specifications.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Lnvillincome	√	√	√	√	√
Inequality/inequality_b	√	√	√	√	√
Rural and daysbreak		√	√	√	√
Demographic variables			√	√	√
Vill_work_soe and vill_work_collective					√
Year fixed effect	YES	YES	YES	YES	YES
Provincial fixed effect	NO	NO	NO	YES	YES

distribution shift directly is difficult, we adopt different indicators to capture the key features of income distribution. The first set of indicators are *inequality* and *inequality_b* defined above. While *inequality* measures the income dispersion across all the households, *inequality_b* focuses on the households below the average income. Hence, the latter provides evidence on the potential impact of poverty-alleviation policies, which reduce the inequality among lower-income households by pulling the extreme poor out of poverty. The second set of indicators are the share of population below certain income levels, expanding on Auffhammer and Wolfram (2014). Holding the average income fixed, communities with higher share of population below the income cutoff have less-equal income distributions.

4.1. Income distribution shifts measured by inequality and inequality_b

We adopt five models to estimate the impact of inequality on appliance penetration rate (Table 2). Our main specification (Model 1) follows Auffahammer & Wolfram (2014), only controlling income alongside the inequality measure (*inequality* or *inequality_b*). Under the assumption of normal distribution, income and inequality fully summarize the income distribution. While simple and straightforward, this specification suffers from omitted variable bias, as other variables such as education and household size – correlated with income – also influence households' decisions on purchasing appliances. To be more specific, infrastructure environment such as electric access and provision of power supply has positive impact on appliance ownership (Auffhammer, 2014; Rong & Yao, 2003). In a number of literatures, demographic features including education level, dwelling features, household composition, race, employment status etc., are examined and found to affect the appliance ownership significantly (Leahy & Lyons, 2010; Matsumoto, 2016; O'Doherty et al., 2008; Rao & Ummel, 2017; Rong & Yao, 2003). To control other confounding factors, we add factors on enabling environment in Model 2 and demographic features in Model 3.

More specifically, Model 2 controls whether the community is urban or rural (*rural*) and how many days a week the community experiences electricity blackout (*daysbreak*). Both variables capture heterogeneities in infrastructure across communities. If the electricity grid does not function reliably, households would have less incentive to buy appliances, as their ability to use them are limited. The rural indicator captures more general gaps: rural households usually have less access to the market or are less informed. Model 3 controls demographic features of households within the community. In addition to dwelling size, education variables and marriage status, we also control the share of minority ethnic population because some minority groups have very different lifestyles and religious beliefs. All models have year fixed effects to control for the common trend cross communities in appliance ownership.

Model 4 and 5 are specification checks. Model 4 adds provincial fixed effects. Model 5 adds the share of workers employed in stated-owned enterprises (SOEs) and in collectives. Inequality levels are usually lower in communities where more people work for SOEs. As such, controlling this variable would lower the estimate for inequality.

For ease of comparison, we show the coefficients of inequality across specifications and across appliances in Fig. 5. The only difference between panel (a) and panel (b) is the inequality measure: (a) uses *inequality* and (b) uses *inequality_b*. Within each panel, the four horizontal segments represent the appliances: TV, washer, fridge and AC, repsectively. Within each segment, the five dots represent the coefficients from the five specifications in sequence, along with 95% confidence intervals. Full regression tables are provided in the Appendix.

We first discuss the results based on Fig. 5(a). For all the appliances, inequality is estimated to have a significantly negative impact on penetration rate based on our main specifications (Model 1–3). As we add more variables, the coefficients remain negative but the magnitudes are reduced, suggesting the correlation between inequality and added variables. For example, the rural-urban gap has been shown to drive a substantial part of high inequality in China (Xie & Zhou, 2014). As we control for the rural areas (in Model 2), we have implicitly restrict the variations in our inequality measures. Communities with less inequality tend to have high levels of education and better living standards; hence controlling demographic variables also dilutes the effect of inequality.

It can also be found from Fig. 5 that the estimated coefficients of *inequality_b* are larger in absolute values than those of *inequality* under most cases, implying that the inequality among low-income group might have a larger impact on the penetration rate on average. This finding, together with the general negative impact observed, supports the S-shaped curve of appliance adoption where income growth at lower end of the distribution matters more.

Across appliances, the magnitudes of coefficients are similar among TV, washer and fridge, hinting that the S-shaped adoption curves have relatively similar shape. In contrast, the estimated impact of inequality on AC adoption is much smaller (see, for instance, Fig. 5(a)). This is mainly because that the income threshold to adopt AC is much higher (Auffhammer & Wolfram, 2014), while the threshold for adopting other appliances such as TV is substantially lower (Auffhammer & Wolfram, 2014; Rao & Ummel, 2017). Our

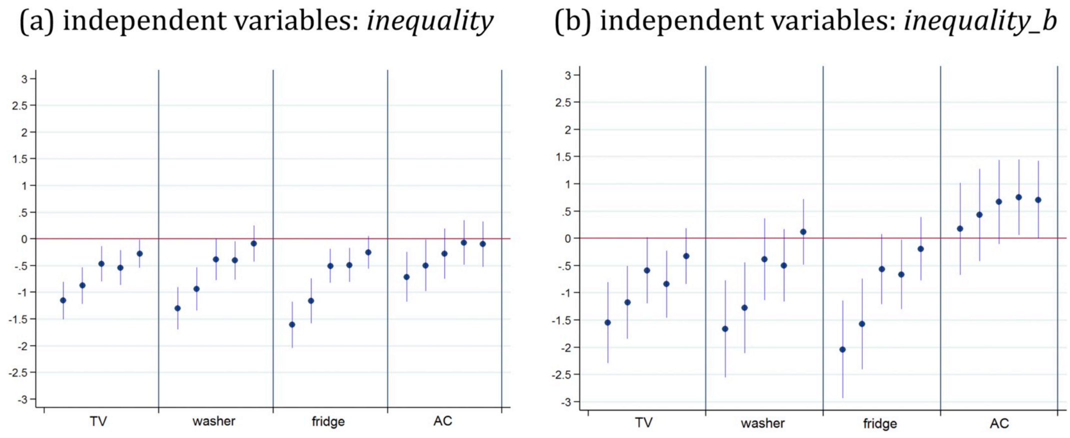

Fig. 5. The impact of inequality on penetration rate.

descriptive analysis also validates this: households adopt ACs the last.

Interestingly, the impact of *inequality_b* is positive on AC. While maybe counter-intuitive, it is theoretically possible to observe positive effect of inequality when the majority of households are below the threshold to adopt. Consider this extreme scenario where each of 10 households in the community has 5000 annual income. Assume the threshold to be 40,000. Nobody buys AC. If instead we allocate all the income to one household (extreme inequality), we would expect the community to buy one AC. In other words, higher inequality leads to higher adoption in this extreme case.

In earlier development stage (pre 2000), China adopted the policy that allows part of the population to get rich first. From our empirical results on ACs and the brief theoretical discussion above, this policy indeed could lead to higher living standard on average. As economy develops, the majority of households have crossed the income threshold. The attention is then shifted to the bottom of distribution, as reducing the inequality among low income families could improve the living standards, represented here by the appliance ownership level.

4.2. Income distribution shifts measured by the share under certain income level

As we noted at the beginning of Section 3, *inequality* and *inequality_b* are measures chosen to represent the distribution shifts. While the way we defined both variables is intuitive, one might argue that our results are dependent upon the measures we chose. Here, we expand on Auffhammer and Wolfram (2014) to use the share of population under a certain income level as the inequality variable. Rather than choosing a specific level of income, we examine a range of possible cutoffs corresponding with the percentiles of the whole income distribution (including all the communities across years). We then calculate, for each community, the share under the percentile (denoted as *sharebelow*). The regression models employ similar specification as Model 1 above, i.e. only controlling income and the *sharebelow*. For each appliance, we ran 99 regressions, with each of them using a different percentile as the cut to calculate the share below. Fig. 6 plots the estimated coefficients of *sharebelow*. The x-axis represents the range of percentiles. The 99 coefficients from 99 different model runs are connected by lines for each of the appliances. The specification of Auffhammer and Wolfram (2014) is a special case in our setting, denoted by 'AW: 3000 RMB' in the graph.

The shapes for TV, washer and fridge are very close, and are consistent with the S-shaped theory. We analyze from the left to the right of the graph. First, if we use the share under very low percentile as the independent variable, the coefficients are estimated mainly among the less developed communities, controlling for year fixed effects. Similar to the earlier discussion on AC, inequality would have a positive effect during this stage, allowing a few people to get rich and adopt the appliances. For a wide range of percentiles (10–40), the coefficients before *sharebelow* stay relatively stable: roughly −3 for TV and washer and −5 for fridge. For percentiles (40–90), the share below the percentile does not clearly correspond with inequality. At higher percentiles, the higher the *sharebelow*, the lower the share in the richest quantile, hence the higher the adoption rate. While our focus has been mostly on the poor, it is worth pointing out that the marginal adoption rate of the rich is also close to zero based on the S-shaped curve. Our empirical evidence supports this theory.

As the adoption rate of AC at the end of our sample period is below 100%, we only observe part of the effects based on S-shaped adoption theory. In other words, most of the households we observe would be considered too 'poor' to adopt ACs. At around 95 percentile, we observe the turning point for AC, suggesting similar pattern for AC may exist if we observe more richer households in the data.

The turning points in the curves are particularly interesting. Theoretically, let us assume that the S-shape curve has a single income threshold (y_s). If we use this threshold in calculating the *sharebelow*, we would observe the highest impact of *sharebelow* in absolute value, as other income cuts we use 'misclassifies' some households. Put in another way, among the income cuts that could measure the dispersion in income distribution, the one using the true threshold would be most effective. The R^2 of the models are also the highest at the turning points.

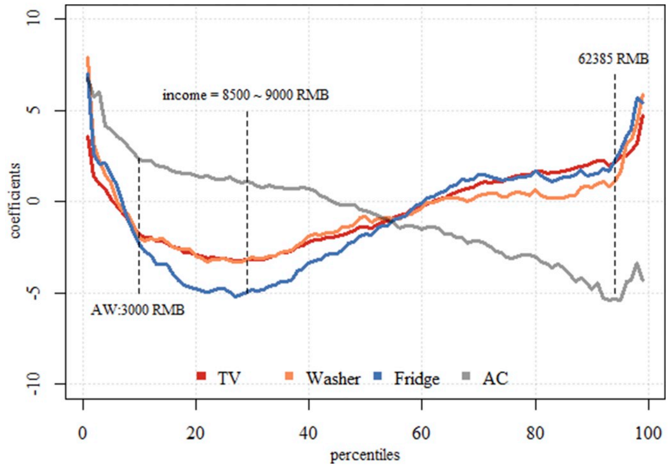

Fig. 6. The impact of inequality on penetration rate using different percentiles.

The dashed lines (pointing up from the curves) highlight the turning points. For TV, washer and fridge, the thresholds are very close, around 8500–9000 RMB. In China, these three appliances are considered essential, and are usually adopted at around the same time. This explains why we do not observe a huge difference in thresholds. ACs, on the other hand, are very different, requiring a much higher annual income level (> 60,000 RMB) to start adopting.

To sum up, the analysis using income percentiles are helpful in two folds. First, it confirms the finding from Auffhammer and Wolfram (2014) and the findings based on inequality measures in Section 3.1. Except for the very earlier development stage where most people are extremely poor, income inequality has statistically significant negative impacts on appliance penetration rate. Second, it quantifies the income thresholds for appliance adoption, which could further improve the prediction of appliance ownership rate.

4.3. Simulation results

We have shown in Sections 3.1 and 3.2 that inequality has negative impact on appliance adoption unless the communities are at the initial development stage. In other words, the sign before the inequality variable verified the S-shape adoption theory established in the literature. What about the magnitudes? Do shifts in income distribution lead to substantial changes in penetration rate? In this section, we aim to provide insights on the magnitudes through two simulations. Before proceeding, we would like to note that these simulations are based on very strong assumptions. While the assumptions are motivated by existing policies, the results are not ready for policy recommendations as the complexities in reality far exceed what we could handle with our reduced-form structure. Nonetheless, they are important exercises to help us understand the magnitudes of coefficients from the estimation models, and think through under what circumstances the inequality factor would be more important.

In all the simulations, we use washer to represent appliances, the results for TV and fridge would be very similar, while the impacts for AC would be smaller based on estimates shown above. Among the model specifications, we use Model 1 that controls only income and inequality, as other control variables interact with income and inequality in complicated ways.

4.3.1. Poverty alleviation

Fighting poverty remains to be a key challenge around the world. China, among others, has contributed to the impressive strides on poverty reduction, alleviating 800 million people out of extreme poverty since 1980s.[12] Moreover, China has pledged to eradicate poverty by 2020–10 years ahead of the goal set by the United Nations Sustainable Development Goals.[13] With dramatic decrease in population living in the bottom of income distribution, keeping other factors constant, we would expect an increase in appliance penetration rate with lower inequality levels.

Our first simulation examines the impact of poverty alleviation. We use income distribution from 2011, the latest year in our survey. For a given poverty line, our first scenario assumes the income of the poor (below poverty line) to be lifted to the poverty line. While reducing the inequality level, the income will also slightly increase under this scenario. To separate out the impact of inequality, we introduce two types of redistribution. In scenario 2, the top 20% of the income distribution provide the income necessary, while in scenario 3, everyone above the poverty line pays equally (including the top 20%). The baseline is no change at all.

Fig. 7 summarizes the results for assumed poverty lines from 1000 to 20,000 (RMB) based on annual income. The three scenarios are represented by red, orange and blue bars respectively. The grey '+' shows the baseline. The official poverty line in China is 2300 RMB in 2011 and 2800 RMB in 2015, both shown in grey vertical lines.

[12] https://www.worldbank.org/en/news/speech/2017/12/07/from-local-to-global-china-role-global-poverty-reduction-future-of-development

[13] https://www.globalcitizen.org/en/content/china-end-poverty-2020/

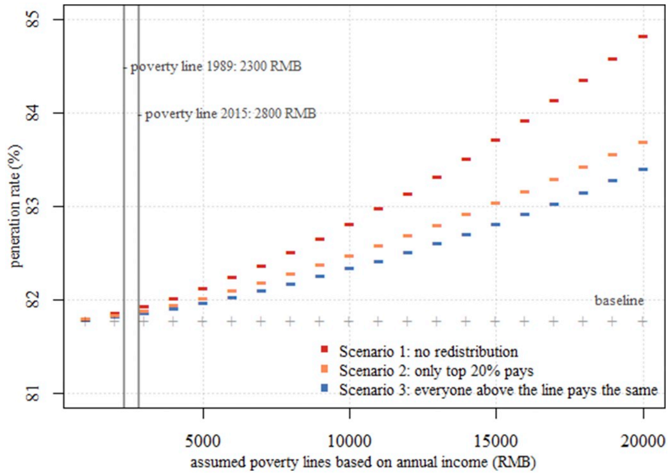

Fig. 7. Simulations of poverty alleviation based on 2011 income distribution.

We highlight three observations from the simulation results. First, the magnitudes of change is < 3% in penetration rate in all cases, even with poverty line assumed to be as high as 20,000 RMB. This reinforces our earlier argument on the thresholds of appliance adoption. Poverty lines below the thresholds of 8500–9000 RMB would not result in much increase in appliance adoption from the poor. In particular, under current poverty lines as low as 2800 RMB, the impact is negligible. Second, the impact increases with the poverty line. As we increase the poverty line, more poor households benefit from the program and the income increases by a larger magnitude for the poor. Third, inequality accounts for roughly half of the effects. To get this, notice that scenario 1 allows for both income and inequality changes, while scenario 2 and 3 fixes the mean income. Hence, Scenario 2 and 3 represents the impact from inequality improvements. If only the top 20% pay, the inequality improvement is larger than if all the people above the poverty line share the responsibilities, and so the penetration rate under scenario 2 is slightly higher.

Taken together, inequality improvement from poverty alleviation leads to limited improvement in penetration rate. This result needs to be interpreted with caution, as the small magnitude may be a result of already high penetration rate in general. Indeed, if we apply the same method but use the income distribution of 1989 as the base year, the magnitudes of impact are much larger (Appendix Fig. S4). As we mentioned earlier, though owning appliances signals higher living standards, it is not the targeted outcomes for poverty alleviation policies. Improvements in health and education would dominate the benefits. That said, if catching up with the rest of China in terms of living standards is important for the poor, the current poverty lines are too low to make a difference in adopting appliances.

4.3.2. Income growth with different distributional changes

In the simulations above, we use only one-year data and do not consider the changes across time. This section incorporates the income growth and examines the penetration paths under different income-distribution changes. We start with year 1989 and assume the income to grow at the average annual growth rate we observe in the sample, i.e. 6%. Along with the same growth in average income, the income distributions have three different paths. For simplicity, we adopt normal distribution and the inequality changes as the standard deviation of the normal distribution changes. Path 1 assumes the standard deviation of income distribution (SDID) to be the same as that of 1989. Path 2 assumes the SDID to decrease to the level of 25 percentile observed in the sample, and path 3 assumes the SDID to increase to the level of 75 percentile.

Fig. 8(a) shows the assumed income distributional changes and the solid lines in Fig. 8(b) show the corresponding paths in penetration rate for washer. Compared with no distributional changes (path 1), the penetration of washer is slightly higher if inequality decreases (path 2) and lower if inequality increases (path 3). To put it another way, under a development path where income grows faster for the poor compared to the rich, communities would reach a certain penetration rate quicker. In the long run, income growth dominates. While the impacts of inequality on penetration paths are very limited in the context of high economic growth in China, the potential magnitudes could be much larger for other less developed economies. For instance, under 2% income growth rate, the penetration rate for a community with increasing inequality would be 20% lower than that with similar level of inequality, given the same 2% growth in income. This highlights the importance of inclusive growth that prioritizes poverty reduction in less developed economies.

5. Conclusion, limitation and future steps

Many existing studies on appliance ownership or household energy consumption focuses solely on income levels, but do not consider the income distribution. To understand the potential bias of neglecting income distribution in energy modeling and forecasting, this study attempts to fill the gap through employing micro-level data and self-constructed inequality indexes. We use panel data at the community level to investigate the impact of income inequality on appliance penetration rate. Across specifications and

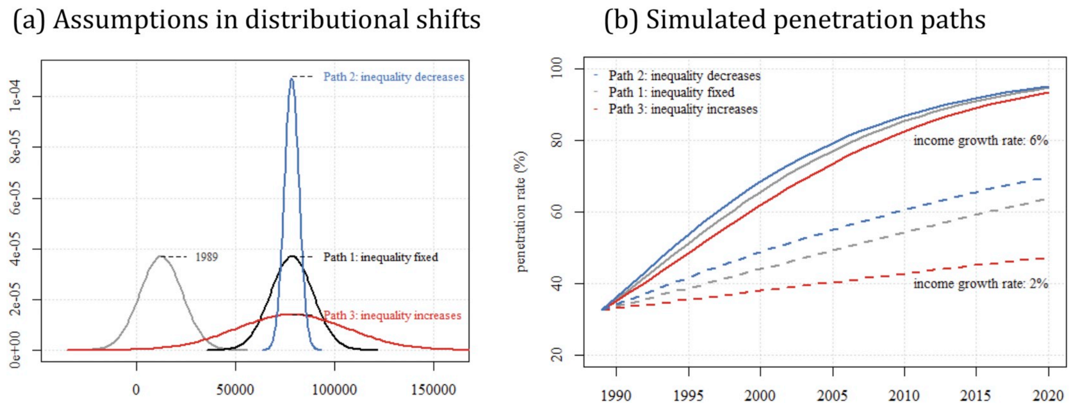

Fig. 8. Income growth with different distributional changes.

appliance types, our diffusion models show that income inequality generally has a negative impact on appliance penetration rate. Moreover, the magnitudes of coefficients are similar among TV, washer and fridge, hinting that the S-shaped adoption curves have relatively similar shape, while the estimated impact of inequality on AC adoption is much smaller, which is due to the much higher income threshold to adopt. The analysis using income percentiles further confirms these findings and quantifies the income thresholds for appliance adoption, which could help improve the prediction of appliance ownership rate.

Under the background of huge poverty alleviation efforts in China and the worldwide pressure to achieve the Sustainable Development Goals (SDGs), we simulate the possible effects of poverty alleviation to understand the magnitudes of our estimates, and provide some initial policy insights. In the context of unmatched economy boom under reform and opening policies, our simulation results suggest that inequality plays a relatively limited role in China. Nonetheless, alternative assumptions with lower income growth rate demonstrate that inequality could be more harmful for regions and countries at an earlier development stage. As appliances are important intermediary to consume services such as cooking, entertaining, heating and cooling, the levels of appliance ownership reflect households' abilities to satisfy basic needs in a modern society. Hence, our results also call for countries to prioritize poverty reduction and to grow more inclusively to raise the living standards of their people.

This study is not without limitations. First, the ownership of each appliance is analyzed independently as in the literature for simplicity, while it is possible that the households who own a particular appliance will be more likely to own another type of appliance due to, e.g., the consumption inertia. Couples also tend to get the basic appliances shortly after getting married, some of which are gifted by relatives and friends. It would be interesting to investigate the joint ownership of multiple appliances and to separate the effect of marriage in the further research. Second, our analyses ignore the complicated interactions between inequality and other socio-economic variables. As noted earlier, the root of inequality is complex and many studies have attempted to explain the levels of inequality using factors including rural/urban division, geographical gaps, education and family types. Building multi-stage dynamic models could potentially improve our analyses, but it is beyond the scope of this study. Third, and related to the second point, our simulation results are based on strong assumptions. Though helpful to provide initial insights, these results need to be accompanied by detailed modeling of a particular policy to provide sound policy recommendations.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2019.101309.

References

Aghion, P., Caroli, E., & Garcia-Penalosa, C. (1999). Inequality and economic growth: The perspective of the new growth theories. *Journal of Economic Literature, 37*(4), 1615–1660.

Alesina, A., & Perotti, R. (1996). Income distribution, political instability, and investment. *European Economic Review, 40*(6), 1203–1228.

Auffhammer, M. (2014). Cooling China : The weather dependence of air conditioner adoption. *Frontiers of Economics in China, 9*(1), 70–84.

Auffhammer, M., & Wolfram, C. D. (2014). Powering up China: Income distributions and residential electricity consumption. *American Economic Review, 104*(5), 575–580.

Boushey, H., & Weller, C. E. (2008). Has growing inequality contributed to rising household economic distress? *Review of Political Economy, 20*(1), 1–22. https://doi.org/10.1177/0891242402239196.

Cao, J., Ho, M. S., Li, Y., Newell, R. G., & Pizer, W. A. (2017). Chinese residential electricity consumption: Estimation and forecast using micro-data. *Resource and Energy Economics, 56*, 6–28.

Cingano, F. (2014). Trends in income inequality and its impact on economic growth. *OECD Social, Employment and Migration Working Papers, No. 163*OECD Publishinghttps://doi.org/10.1787/5jxrjncwxv6j-en.

Day, R., Walker, G., & Simcock, N. (2016). Conceptualising energy use and energy poverty using a capabilities framework. *Energy Policy, 93*, 255–264.

Farrell, M. (1954). The demand for motor-cars in the United States. *Journal of the Royal Statistical Society, 145*(3), 171–201.

Fell, M. J. (2017). Energy services: A conceptual review. *Energy Research & Social Science, 27*, 129–140.

Gan, L. (2013). Income inequality research from China Household Finance Survey. *Journal of Translation from Foreign Literature of Economics, 2013*(04), 41–57 (in Chinese).

Gertler, P., Shelef, O., & Wolfram, C. (2016). The demand for energy-using assets among the world's rising middle classes. *American Economic Review, 106*(6), 1366–1401.

Hsieh, C. C., & Pugh, M. D. (1993). Poverty, income inequality, and violent crime: A meta-analysis of recent aggregate data studies. *Criminal Justice Review, 18*(2), 182–202.

Hunt, L. C., & Ryan, D. L. (2015). Economic modelling of energy services: Rectifying misspecified energy demand functions. *Energy Economics, 50*, 273–285.

International Energy Agency (2019). IEA world energy balances 2018. https://www.iea.org/statistics/, Accessed date: 15 April 2019.

Keeley, B. (2015). *Income inequality: The gap between rich and poor.* OECD Insights: OECD Publishing, Paris.

Leahy, E., & Lyons, S. (2010). Energy use and appliance ownership in Ireland. *Energy Policy, 38*(8), 4265–4279.

Li, H., & Zhu, Y. (2008). Income, income inequality and health: Evidence from China. *Understanding inequality and poverty in China* (pp. 137–172). London: Palgrave Macmillan.

Li, S., & Luo, C. L. (2011). How unequal is China? *Economic Research, 46*(04), 68–79 (in Chinese).

Matsumoto, S. (2016). Household income structure and electrical appliance ownership: Evidence from Japanese national household survey. *International Journal of Energy Economics and Policy, 6*(1), 14–19.

McNeil, M. A., & Letschert, V. E. (2010). Modeling diffusion of electrical appliances in the residential sector. *Energy and Buildings, 42*(6), 783–790.

O'Doherty, J., Lyons, S., & Tol, R. S. J. (2008). Energy-using appliances and energy-saving features: Determinants of ownership in Ireland. *Applied Energy, 85*(7), 650–662.

Pereira, M. G., Freitas, M. A. V., & da Silva, N. F. (2011). The challenge of energy poverty: Brazilian case study. *Energy Policy, 39*(1), 167–175.

Rao, N. D., & Ummel, K. (2017). White goods for white people? Drivers of electric appliance growth in emerging economies. *Energy Research & Social Science, 27*, 106–116.

Rong, Z., & Yao, Y. (2003). Public service provision and the demand for electric appliances in rural China. *China Economic Review, 14*(2), 131–141.

Ürge-Vorsatz, D., et al. (2012). Chapter 10 – Energy end-use: Building. *Global energy assessment – Toward a sustainable future* (pp. 649–760). Cambridge, UK: Cambridge University Press [and New York, NY, USA and the International Institute for Applied Systems Analysis, Laxenburg, Austria].

Wang, P., Pan, J., & Luo, Z. (2015). The impact of income inequality on individual happiness: Evidence from China. *Social Indicators Research, 121*(2), 413–435.

Xie, Y., Zhang, X., Xu, Q., & Zhang, C. (2013). In Y. Xie, X. Zhang, J. Li, X. Yu, & Q. Ren (Eds.). *Wellbeing development report of China* (pp. 27–53). Beijing: Peking Univ Press (in Chinese).

Xie, Y., & Zhou, X. (2014). Income inequality in today's China. *Proceedings of the National Academy of Sciences of the United States of America, 111*(19), 6928–6933.

Yu, X., & Xiang, Z. (2014). Income inequality in today's China. *Proceedings of the National Academy of Sciences of the United States of America, 111*(19), 2–3.

Yue, X. M., & Li, S. (2013). Gini index: True or false? *South Reviews, 5*, 65–67 (in Chinese).

Zhou, S., & Teng, F. (2013). Estimation of urban residential electricity demand in China using household survey data. *Energy Policy, 61*, 394–402.