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Efficiency Snakes and Energy Ladders: A (meta-)frontier demand analysis of electricity consumption efficiency in Chinese households

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EFFICIENCY SNAKES AND ENERGY LADDERS: A (META-)FRONTIER DEMAND ANALYSIS OF ELECTRICITY CONSUMPTION EFFICIENCY IN CHINESE HOUSEHOLDS

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ABSTRACT

Policy makers presently lack access to quantified estimates–and hence an explicit understanding–of energy consumption efficiency within households, creating a potential gap between true efficiency levels and the necessarily assumed efficiency levels that policy makers adopt in designing and implementing energy policy. This paper attempts to fill this information gap by empirically quantifying electricity consumption efficiency for a sample of more than 7,000 households. Adopting the recently introduced frontier demand function due to Filippini and Hunt (2011) but extending it into the metafrontier context–to control for structural heterogeneity arising from location type–it is shown that consumption efficiency is little more than 60% on average. This implies huge potential for energy reduction via the expansion of schemes to promote energy efficiency. City households, which are the wealthiest in the sample, are shown to define the metafrontier demand function (and hence have the potential to be the most efficient households), but at the same time exhibit the largest inefficiencies. These facts together allow for a potential refinement on the household energy ladder concept, suggesting that wealth affords access to the best technologies thereby increasing potential energy efficiency (the 'traditional' view of the household energy ladder), but complementary to this these same households are most inefficient. This has implications for numerous areas of policy, including for example the design of energy assistance schemes, identification of energy education needs/priorities as well more refined setting of subsidies/tax-credit policies.

JEL Classifications: D12; Q41; Q48; R22.

Key Words: Energy consumption efficiency; Frontier demand function; Chinese households.

Efficiency Snakes and Energy Ladders: A (meta-)frontier demand analysis of electricity consumption efficiency in Chinese households.

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1. Introduction

A carefully obtained empirical snapshot of energy consumption efficiency at the level of individual households has the potential to inform numerous areas of policy, including for example the design of energy assistance schemes, identification of energy education needs/priorities and a framework for more informed allocation of energy subsidy and tax-credit policies. However to date, as far as is known, such a picture has not been obtained for households. Two reasons can be offered as to why this is so: first is that the methods and techniques used to acquire such information (namely frontier demand functions) were only set out very recently in Filippini and Hunt (2011, 2012); second is that household level datasets, for various legitimate reasons, often fail to collect sufficiently rich information on energy as well as a wide enough range of socioeconomic variables to describe consumption patterns using economic concepts and theories. Notwithstanding a general absence of household level data, hypotheses have been presented regarding a concept referred to as the 'household energy ladder' (see for example Hosier and Dowd (1987) or more recently van der Kroon et al. (2013)), which suggests wealthier households have greater efficiency potential via their ability to purchase newer and more energy efficient home appliances.

When analyzing households there are often important sources of structural heterogeneities that can help inform the empirical framework for analysis. Differences in urban form, such as the differences among cities, towns and villages, are commonly associated with different lifestyle opportunities due among other things to the various agglomeration economies, and increased access to public goods, that can occur in larger populations. Numerous studies have alluded towards the implications of such features on the consumption of energy, see for example Chen and Song (2008), Peters et al. (2007), Hubacek et al. (2009) and more recently Yan (2015) in the case of China. Thus in seeking to provide an empirical benchmark on the level of household energy consumption efficiency, households from cities, towns and villages should not be immediately compared with each-other, and instead the efficiency in each location type should in the first instance only be compared to other households in similar location types.

It is however conceivable that a more general comparison may still be possible, encapsulating a notion of comparison that embeds spillover effects, and is independent of urban form. This will be explicitly handled in the empirical phase of the work by utilizing meta-frontier methods described by Battese and Rao (2002), described in more detail in the literature review and methodology sections. In brief, the metafrontier methodology can be thought of as a natural extension to traditional frontier methods, which would in the present case impose the underlying assumption that all consumers adopt an identical demand function - e.g. a single function which a single associated frontier. In the real world it is more likely that consumers are more heterogeneous than this, giving rise to the possibility that facets of consumer behavior such as price and income elasticities might reasonably be expected to vary across sub-groups of society, and accordingly that a separate frontier exists for each sub-group. This paper therefore uses the meta-frontier method to address this issue, allowing for each group to adopt its own demand function and associated frontier but additionally providing a means to make higher-level comparisons across each of the sub-groups.

The empirical context for the study is cast in terms of a sample of Chinese households (for the year 2012). It is contended that this is an ideal dataset to propagate baseline understandings of energy consumption efficiency relevant to many parts of the world. For example, although it is true that there are many unique features of a Chinese lifestyle that do not easily transfer to other economic contexts, the country presently has what is arguably the most complete representation of household types compared to any other market context. The most affluent households in China are among the most affluent in the world, and the more developed cities including for example Beijing and Shanghai have characteristics common to any international city. At the other end of the spectrum, rural life in China is in cases akin to the same concepts of poverty and deprivation witnessed in many far less developed economies. In between these two extremes is a population which ranges across varying income and educational levels, with differing balances of household structure etc. Accordingly insights can be derived that have some possible resonance in almost any other market context.

The main contributions of the study derive from several important departures from existing works and can be summarized as follows: First is that the concept of the 'frontier demand function' is applied to household level data, making this as far as is known the first study to attempt this; second is the extension into the metafrontier context, allowing for important structural heterogeneity accruing to urban form effects to be explicitly modeled; third is that an error-component stochastic frontier model is utilized to help ensure accurate identification of efficiency levels. It is found that the average Chinese household operates at about 63% efficiency, and only around 7% of households achieve an efficiency level of 80% or higher. Thus there exist clear opportunities to implement household efficiency management policies and have a major impact on energy consumption levels across China. Regarding the 'champions' of efficiency, among the top 5% of the most efficient households, only 22% are from the city, the remaining being from towns (20.6%) and villages (57.4%).

The results are rich and among other things allow for an enhanced understanding of an empirical phenomenon known as the 'household energy ladder'. The conventional wisdom behind the energy ladder argues that higher income households will be able to access more efficient technologies, and is a phenomenon that has found empirical support, as for instance discussed in Hosier and Dowd (1987), Leach (1992), Kirk et al. (1994) and more recently Hiemstra van der Horst and Hovorka (2008) and van der Kroon et al. (2013). The results contained in the present paper do not challenge the existence of the energy ladder, but offer an enhanced perspective by illustrating that the consumption *efficiency* of the relatively richer city households is in fact much lower than in poorer households within towns and villages. Thus efficiency gains that may arise from 'climbing the energy ladder' may be negated by lower efficiency in consumption behaviour - e.g. purchasing energy efficient light bulbs but taking less care to turn them off when they are not needed. This has clear implications for policy design.

The paper is structured as follows: Section 2 discusses the related literate; In section 3 the data used in the analysis–the Chinese Family Panel Survey–is described; The empirical framework and econometric methodology are presented in section 4; Section 5 provides a general discussion of the results; lastly Section 6 concludes the paper.

2. Literature Review

Empirical economic (econometric) models of energy consumption first appeared in the academic literature in Houthakker (1965),[1] and were followed by high profile studies including Halvorsen (1975) among others. In these early studies, unsurprisingly, the emphasis was on obtaining informative (both economically and statistically) estimates of price and income elasticities. The notion of efficiency of energy consumption did not seem to make its first appearance until Hartman (1979) who openly discusses the importance of energy efficiency, but did not try to empirically quantify it.

There has been a dramatic growth in empirical literature discussing, and more importantly quantifying various dimensions of efficiency, predominantly in the context of a production function, since Aigner et al. (1977) outlined statistical procedures to capture such information, namely the stochastic frontier analysis method.[2] Typically these types of study concentrate on modeling a definition of total factor productivity with a view to answering questions of the type 'is a firm creating the best level of output given the resources it is using'.[3] If this is not the case a firm is regarded as being inefficient.

Energy and resource economists quickly picked up on the idea that a production function can be re-written to ask the more direct question of how efficiently an energy input is being used within the process of producing economic output, see for example: Boyd and Pang (2000), Hu

[1]To the best of our knowledge there were no published studies prior to this.

[2]In addition to stochastic frontier methods (SFA) which emerged during the 1980's; there also exist widely used non-parametric Data Envelopment Analysis (DEA) techniques. SFA has proved popular, since in addition to measuring efficiency it also allows for explicit estimation and characterization of the frontier itself, which DEA does not.

[3]This is the notion of output efficiency, a related concept of cost efficiency ask 'if a firm is creating the current level of output at the lowest cost'.

and Wang (2006). While informative, these types of study are inherently focused on the behaviors of firms, and therefore do not portray how effectively energy may be being used within the household sector. Filippini and Hunt (2011, 2012) and Filippini and Zhang (2013) among others, offer an alternative view of energy efficiency that is grounded in the nature of an aggregate energy demand function. To be more precise Filippini and Hunt (2011) introduced the concept of 'frontier energy demand functions', which extend traditional econometric/empirical demand functions to account for the explicit desire by a household to minimize its consumption of energy (and hence the cost of using energy services). Within the context of frontier demand models the frontier defines the minimum level of energy that a household can reasonably consume, given the resources it has, which will be either equal to or less than the actual level of consumption, but not above it.

Figure (1) provides a visual illustration of the concept of a 'demand frontier'. This graph plots a demand curve ($Q = f(P, Y, Z)$), which illustrates the property of having a rate of consumption (Q) that increases (at a decreasing rate) with the household inputs including income (Y), prices[4] (P) and 'other' factors (Z). This demand is therefore contingent on the inputs. There exists a true/global minimum energy required (MER^*) e.g. for basic living/sustenance needs, reflected by the dashed line, while the demand curve itself represents the input-contingent MER. Point A^* reflects a household that uses the 'right' level of energy resources given their household characteristics, but it is possible given the same resources that the same household could have in fact consumed more energy at for example point A. At this point the household is overconsuming energy, and is hence inefficient. Similarly the household at point B is fully efficient but the one at point C is not. Filippini and Hunt (2011, 2012) describe how existing stochastic frontier analysis methods can be used to measure the distance between actual consumption and the MER, and thus measure efficiency, for US states and European countries respectively.

[4] This graph is for illustrative purposes only. The discerning reader may harbor concerns that demand appears to be increasing in price, but then should keep in mind that the function relating the variables is not defined, and by assumption the price component would perhaps appear inversely within the function.

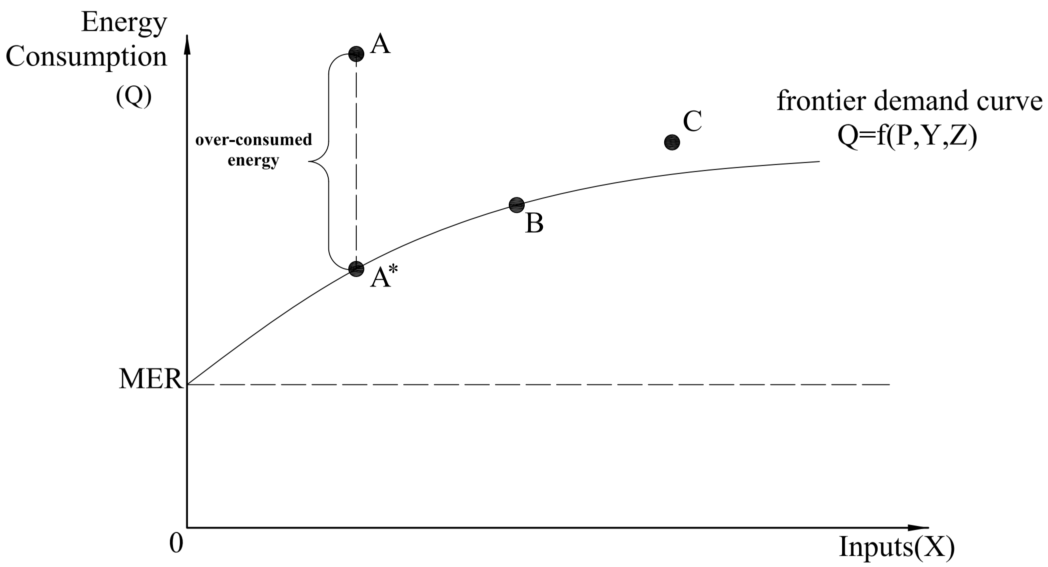

Figure 1: Illustration of a frontier demand function and the MER

China has become a focus of empirical interest in recent years, as a result of prodigious growth in national income, personal wealth and a massive growth in energy consumption. There is a large and growing body of literature quantifying various aspects of energy efficiency for China including: Bennett et al. (2002); Lu (2006); Chen and Song (2008); Zhou et al. (2008); Wang et al. (2013); Feng et al. (2010); Zhou et al. (2012); Zhang et al. (2013); Zhang et al. (2014); Yao et al. (2015); Lin and Du (2015) among others. These studies contain many rich insights of great importance to policy discourse, but in brief none of them give any clear description of the nature of energy consumption in China at the household level and by consequence.

Looking more widely across the literature, the absence of household level estimates of energy consumption efficiency is not restricted to the case of China. It is fair to say that this has alluded the literature in general. Whilst it is true that engineering based paradigms of household level energy consumption have been discussed in various different papers, including among others: Liu and Myers (2000); Reddy (2003); Boardman (2004); and Oikonomou et al. (2009).

These studies/methods describe an 'engineering potential' of the minimum level of energy consumption possible given the parameters of a house including size, asset ownership (TV, fridge, etc.), asset age and so forth. This can then be compared against actual energy consumption, and the difference offers a measure of one type of efficiency. This however differs from the type of efficiency described in Filippini and Hunt (2011), and more generally the type of efficiency that economists place a greater emphasis on. Economic notions of efficiency do not require engineering potential to be the benchmark for efficiency calculation, and benchmark against similar individuals to place a lower bound on the level of energy that could be consumed given the observed 'best-practice'. Ideally this would be the same as the engineering potential, but idiosyncrasies in the ways humans interact and live, even within the workplace, often make this unlikely. It can therefore be established that an initial inquiry into the nature of energy consumption efficiency at the household level helps to fill a general void in the literature.

As discussed in the introduction section of this paper, there is an obvious interest in attempting to account for the structural heterogeneities that differentiate cities, towns and villages in a country such as China. To this end the metafrontier methods described by Battese and Rao (2002) and O'Donnell et al. (2008) among others are adopted. Examples of metafrontiers applied to energy efficiency include for example Chen and Song (2008), Lin and Du (2013) and Wang et al. (2013) among others. In the present context the metafrontier concept reflects the idea that city households are sufficiently unique compared to town and village households, and thus that city households should at first be only compared against other city households. However at a more fundamental level, a house is a house, and people are people, thus it is not beyond reason that for example a household in a town could not be compared to a city household, or in fact a village household. In the concept of spillover literature (e.g. Bernstein (1988); Coe and Helpman (1995); Audretsch and Feldman (1996) and Cohen et al. (2002)), it could be argued that there are intangible characteristics, including lifestyles, social norms and cultures etc. that may be transferable across any household type–justifying that lessons can be learned by any household from across the full population and hence that an additional benchmark reference frontier exists as the envelope around all household types. The mechanics of this are discussed in detail after first describing the data used in the analysis in the next section, but in brief the metafrontier method allows this idea to be implemented and provides a lot of additional policy relevant information.

3. Data and Methodology

The data used in this study are taken from the Chinese Family Panel Survey (CFPS) which is conducted by the Institute of Social Science Survey (ISSS) at Beijing University. This is the same data source as used for example by He and Reiner (2016). The data, which are for the year 2012, is based on a survey of more than twelve thousand households across China[5]. The survey offers the advantage of a nationally representative snapshot of households in China, but although it is conducted across 25 different provinces[6], is not intended to be provincially representative. The primary reason for choosing this dataset is that it directly records electricity consumption along with a wide enough range of household characteristics to support a rich and meaningful statistical analysis from a single and consistent source of data.

Within the CFPS data 67% of households are from villages, however according to the Chinese National Bureau of Statistics (NBS), the urbanization population in 2011 should be 51.27% of the total population.[7] Thus, though the CFPS claims to be nationally representative, it should be kept in mind when interpreting the results that city and/or town households may be under-represented.[8] Due to various elements of missing data,[9] the final sample size available for estimation includes 7,102 households. To avoid outlier behaviors from impacting upon the modeling results this simple is restricted to households that do not use electricity for business purpose, do usually live at home (e.g. are not part of the transitory migrant population) and have 'reasonable' electricity consumption levels. 'Unreasonable' consumption excludes a small

[5]Further information and access to the data can be found at "www.isss.edu.cn/cfps/EN/About/".

[6]The 25 provinces are Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Jiangxi, Shanxi, Liaoning, Jilin, Heilongjiang, Anhui, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shanxi and Gansu.

[7]Sourced from "http://www.stats.gov.cn/tjsj/ndsj/".

[8]It is difficult to be sure which of the CFPS or NBS sampling schemes are more accurate, only that they differ. There is an argument that this could be a source of bias in the analysis, however the extent to which this can be either proved/dis-proved or remedied within the empirical work falls outside of the scope of this paper. We appreciate comments provided by an anonymous referee to make this point more clearly.

[9]Checks on the variables that are fully observed across all households, suggests that although many households are dropped, the general distributions of the variables remain the same, with broadly similar means/variances and also similar minima and maxima.

number of observations where electricity consumption is less than 10 kwh per month or over 1,000 kwh for domestic usage only.

A range of socioeconomic variables, household characteristics and area/regional controls are included, each of which is defined in Table 1,[10] while Table 2 offers some simple descriptive characteristics of these variables. Though not discussed here in length, the presence of these variables will be important in the modeling phase of the work to account for variations in energy consumption that would be expected to arise in for example larger or richer households, households with children, or households which own TV's, refrigerators etc. A quick glance at the characteristics across cities, towns and villages illustrates the fact that affluence increases moving from the village to the city. Following Eakins (2014) household expenditure is used as a proxy for household income, as it tends to be more accurately reported.

[10]Further variables that were considered for estimation, following for example Filippini and Zhang (2013) among others, include measures for heating degree days (*hdd*) and cooling degree days (*cdd*) across the provinces, which provide proxy measures for the impact of weather conditions. These measures are available at a provincial level only, and when attempting to incorporate into the empirical model create sufficient collinearity with the province level fixed effects as to cause optimization failures hence are omitted here. This only occurs due to the absence of multiple waves of data, and both *hdd* and *cdd* should be considered in future studies when later waves become available for use.

Table 1: **Descriptions of the variables included in the analysis**

Variable	Variable description
Socioeconomic characteristics	
Electricity Consumption	Monthly electricity consumption (kwh) of a household for domestic useage only, (logarithm term)
Income Elasticity	Household total expenditure, (logarithm term)
North	The North of China (“1” true, “0” false)
House Size	The size of the living place (square meter)
Automobile	Ownership of the automobiles (“1” yes, “0” no)
Air Condition	Ownership of the air conditions (“1” yes, “0” no)
TV	Ownership of the TV (“1” yes, “0” no)
Mobile	Ownership of the mobile phone (“1” yes, “0” no)
Fridge	Ownership of the fridges (“1” yes, “0” no)
PC	Ownership of the PCs (“1” yes, “0” no)
Ebike	Ownership of the electricity bikes (“1” yes, “0” no)
Washing Machine	Ownership of the washing machine (“1” yes, “0” no)
Motorcycle	Ownership of the motorcycles (“1” yes, “0” no)
Financial Assets	Natural logarithm term of household financial assets, (logarithm term)
Health Poor	Have poor health family members(“1” true, “0” false)
1 child	Have 1 child (“1” yes, “0” no)
2 children	Have 2 children (“1” yes, “0” no)
3 children and more	Have at least 3 children (“1” yes, “0” no)
2 adults	Have 2 adults (“1” yes, “0” no)
3 adults	Have 3 adults (“1” yes, “0” no)
4 adults	Have 4 adults (“1” yes, “0” no)
5 adults and more	Have at least 5 adults (“1” yes, “0” no)
Apartment	House style is an apartment (“1” true, “0” false)
Water Source	The main warter source is well(“1” true, “0” false)
Energy Source	The main energy source is fire-wood(“1” true, “0” false)
Environmental Perception	The severity of the environmental problem in China (varies from “0” not severe to “10” extremely severe, integers only)
Head Industry	Industry field of the family head (there are 20 fields also means 19 industrial variables)
Head Education Level	Education level of the family head (there are mainly 6 levels also means 5 educational variables)
Max Education Year	The maximum education year of a member in the household
Area/regional controls	
Fixed Effects	Provinces (there are 25 provinces, 24 provincial variables, and Beijing is the basic group)
Local Economy	The economic condition of the community (varies from “1” very poor to “7” very rich, integers only)
Local Cleanliness	Cleanliness of roads in the community (varies from “1” very dirty to “7” very clean, integers only)
Social Homogeneity	Socioeconomic homogeneity of the members in community (varies from “1” very low to “7” very high, integers only)
Power Failure Sometimes	Electricity power sometimes off (“1” true, “0” false)
Power Failure Often	Electricity power often off (“1” true, “0” false)

Notes: (1) The definition of ‘North’ refers to the northern provinces that receive free heating from the state, which include Beijing, Tianjin, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Anhui, Shandong, Henan, Shanxi and Gansu.
(2) The 20 alternative industries for the head of household include: Manufacturing, Wholesale and retail, Public management and social organization, Rent and business service, Transportation and warehousing, Culture, sports and entertainment, Education, Finance, Citizen service and other service, Social work, Real estate, Research and technological service, Computer service and software, Architecture, Environment and public service, Power, fuel and water generation and distribution, Mining, Agricultural and fishing industries. “Others” is the base group used in estimation.
(3) Head of households education level may take one of the following categories: No schooling (the base group for estimation), Primary school, Secondary school, High school, 3-year college, 4-year University and above.

Table 2 shows the differences in energy consumption levels among households from cities, towns and villages. In terms of monthly electricity consumption, on averagely city and town households almost consume double the amount of electricity (respectively 141 kwh and 133 kwh) than village households with (76 kwh) per month. This is partly attributable to the fact that almost half of village households still use firewood for cooking–a feature which will be controlled for in the modeling work later. In addition, village households face a higher probability of sometimes finding electricity unavailable (46%) e.g. due to brownouts/temporary blackouts, more so than households in the city and town (30% and 39%, respectively). That upwards of a third of all Chinese households experience power shortages on occasions is indicative of a need for infrastructure upgrades, but also may cause households to be more efficient when they consume in the fear that it may suddenly become unavailable again.

Table 2: **Simple descriptive statistics for variables included in the analysis**

Variable	**Average data values**				**Standard deviations**			
	City	Town	Village	Full Sample	City	Town	Village	Full Sample
Electricity Consumption	141.27	133.20	76.17	97.09	94.69	91.31	70.58	84.24
Socio-economic characteristics								
Expenditure	63,864.50	55,410.90	30,185.30	40,378.45	70,022.73	63,902.92	39,377.59	52,682
Financial Assets	76,556.63	48,599.63	16,568.92	32,824.53	184,985.30	155,035.60	41,960.71	108,889.10
House Size	73.38	101.99	139.71	121.40	41.38	65.64	85.03	80.36
Automobile	0.15	0.17	0.08	0.11	0.36	0.37	0.27	0.31
Air Condition	0.56	0.47	0.17	0.29	0.50	0.50	0.37	0.45
TV	0.97	0.97	0.97	0.97	0.18	0.17	0.18	0.18
Mobile	0.90	0.94	0.90	0.90	0.30	0.24	0.30	0.30
Fridge	0.92	0.83	0.58	0.68	0.28	0.38	0.49	0.46
PC	0.65	0.52	0.19	0.33	0.48	0.50	0.39	0.47
E-bike	0.28	0.33	0.33	0.32	0.45	0.47	0.47	0.47
Washing Machine	0.89	0.86	0.67	0.74	0.31	0.35	0.47	0.44
Motorcycle	0.12	0.33	0.57	0.45	0.32	0.47	0.49	0.50
Health Poor	0.27	0.33	0.44	0.39	0.44	0.47	0.50	0.49
1 child	0.31	0.31	0.30	0.30	0.46	0.46	0.46	0.46
2 children	0.04	0.09	0.16	0.13	0.18	0.29	0.36	0.33
more than 3 children	0.002	0.03	0.05	0.03	0.05	0.16	0.21	0.18
2 adults	0.45	0.43	0.34	0.37	0.50	0.50	0.47	0.48
3 adults	0.26	0.25	0.25	0.25	0.44	0.43	0.43	0.44
4 adults	0.10	0.15	0.23	0.19	0.30	0.36	0.42	0.39
more than 5 adults	0.02	0.07	0.12	0.09	0.15	0.25	0.32	0.29
Apartment	0.79	0.48	0.02	0.24	0.40	0.50	0.14	0.42
Water Source	0.01	0.09	0.48	0.33	0.09	0.29	0.50	0.47
Energy Source	0.01	0.08	0.49	0.34	0.08	0.26	0.50	0.47
Environmental Perception	6.20	5.77	4.77	5.19	2.21	2.13	2.26	2.31
Max Education Year	12.21	11.2	9.03	9.96	3.76	3.91	4.04	4.18
Area/regional controls								
Local Economy	4.33	4.12	3.85	3.98	1.36	1.15	1.30	1.30
Local Cleanliness	4.45	4.23	3.91	4.06	1.32	1.19	1.34	1.33
Local Homogeneity	4.66	4.42	4.17	4.30	1.24	1.25	1.24	1.26
Power Failure Sometimes	0.30	0.39	0.45	0.41	0.46	0.49	0.50	0.49
Power Failure Often	0.01	0.03	0.04	0.03	0.10	0.16	0.20	0.17
North	0.63	0.47	0.65	0.62	0.48	0.50	0.48	0.49

Notes: The number of observation for city, town and village households are 1,366, 1,046 and 4,690, respectively. The full sample is 7,102.

3.1. A brief note on the treatment of prices

Price data are generally not available at the level of household, and moreover city ID codes are withheld by ISSS to help ensure anonymity of household observations. The consequence of this is that only provincial level electricity price data can be matched to the CFPS data. Since however the data are for a single year only, these price measures perfectly correlate with province level fixed-effects that as will be discussed later will be used to control for a range of province specific heterogeneity. Since the main focus of this paper is on quantifying efficiency levels, the absence of uniquely identified price elasticities is not considered a major limitation, but this is an obvious focus for future work once additional waves of the data become available.

We next turn attention to the methodology, describing first the technical aspects of estimating the frontier demand function, after which the econometric treatment of the metafrontier function is described.

3.2. Frontier Demand Functions

In order to accurately identify efficiency, it is necessary to understand the household demand function. The demand function determines the optimal, or minimum, energy requirement given the characteristics of the household. Inefficiency will be somehow determined by the difference between actual consumption and the minimum energy required. As discussed in the literature review, SFA models are not only suitable for this purpose, but specifically designed for this task.

For household i, energy demand Q_i is determined by the prices faced by the household P_i, the level of income Y_i available, as well as a number of additional demand influencing factors and households characteristics $\mathbf{X}_i$, see Eq. (1):

$$Q_i = f(P_i, Y_i, \mathbf{X}_i) + v_i \tag{1}$$

Consistent with the vast majority of empirical energy demand models, a Cobb-douglas functional form is assumed. Denoting the natural log of variables using lower case letters (e.g. $q_i = \ln Q_i$) and also introducing province specific fixed effects α_j, this leads to the following estimable linear function:

$$q_i = \alpha_0 + \beta_1 p_j + \beta_2 y_i + \Pi \mathbf{x}_i + \alpha_j + v_i \tag{2}$$

The set of variables in $\mathbf{x}_i$ includes a range of household characteristics and control variables, such as car ownership, house ownership, number of children within a family, house size and so on, not all of which are expressed in log terms.

Filippini and Hunt (2011, 2012) extend the type of energy demand function in Eq. (2), to explicitly model the role of 'energy consumption efficiency', which they define in the stochastic frontier sense. Precisely Eq. (2) is augmented with the term μ_i whose purpose is to reflect the degree of inefficiency. It is assumed that μ is a strictly positive and individual specific component, that captures how much more energy the household is consuming beyond that which is 'necessary'. The resulting econometric formulation can now be expressed thusly:

$$q_i = \alpha_0 + \beta_1 p_j + \beta_2 y_i + \Pi\mathbf{x}_i + \alpha_j + \nu_i + \mu_i \tag{3}$$

$$\nu_i \sim N(0, \sigma_\nu^2)$$
$$\mu_i \sim N^+(0, \sigma_\mu^2)$$

This specification can be estimated using conventional stochastic frontier methods as described in Aigner et al. (1977). One criticism which might be levied against this specification is that the inefficiency μ_i is simply a half-normal stochastic process. Many scholars have raised questions as to how meaningful the efficiency scores from such a model can be. To alleviate such concerns here the efficiency-effects form of the stochastic frontier model, due to Battese and Coelli (1995), is estimated which estimates the mean level of inefficiency using some additional pre-determined variables in a vector $\mathbf{z}_i$:

$$q_i = \alpha_0 + \beta_1 p_j + \beta_2 y_i + \Pi\mathbf{x}_i + \alpha_j + \nu_i + \mu_i \tag{4}$$

$$\nu_i \sim N(0, \sigma_\nu^2)$$
$$\mu_i \sim N^+(f(\mathbf{z}_i), \sigma_\mu^2)$$

Key to the inefficiency identification strategy is to ensure a meaningful quantification of inefficiency. To do so the variables in $\mathbf{z}_i$ should be expected/chosen to relate to efficiency. For this purpose we include in $\mathbf{z}_i$ variables relating to environmental perceptions (on the premise that households that are aware of the health of the environment will expend greater effort to avoid energy wastage), education level of the head of household (assuming that the household head is responsible for example for appliance purchase and replacement decisions, which may imbue technological inefficiencies) and indicators of energy source reliability (frequency of power failure) and usage experience (whether an electric using household may still use firewood as its main energy source). In practice it is often assumed that the variables in $\mathbf{z}_i$ assume a linear functional form:

$$f(\mathbf{z}_i) = \gamma_0 + \gamma_1 z_{1i} + \gamma_2 z_{2i} + ... \tag{5}$$

The variables in $\mathbf{z}_i$ include: environmental perception, information regarding frequency of power failure, health status, whether a household uses firewood for cooking and/or accesses water from a well (indicating experience with grid supplied resources). In addition information regarding the education level of the head of household is included, but in a slightly different manner than in the demand function itself. The rationale is as follows: if it is assumed that the head of the household is responsible for purchasing decisions within the household, his/her education level may reflect upon the types of technologies (and their efficiency potential) that are purchased, or more generally that the education of other household members may be less likely to influence the baseline efficiency level.

3.3. A metafrontier demand function

As discussed earlier in the paper, steps are required to control for the structural heterogeneity inherent in the comparison of households from different urban forms namely, cities, towns and villages. Households in different location types may feasibly fall under separate frontiers determined by different parameters in a demand function and with different distributions of efficiency (those are how SFA are exhibited in the first subsection). In this regard, the efficiency of an urban household would for instance only be directly comparable to that of other households located in city regions. This implies the need for three separate stochastic frontier models to be estimated, one for each group:[11]

$$q_i^C = \alpha_0^C + \beta_1^C p_i + \beta_2^C y_i + \Pi^C \mathbf{x}_i + \alpha_j^C + \nu_i^C - \mu_i^C \tag{6a}$$

$$q_i^T = \alpha_0^T + \beta_1^T p_i + \beta_2^T y_i + \Pi^T \mathbf{x}_i + \alpha_j^T + \nu_i^T - \mu_i^T \tag{6b}$$

$$q_i^V = \alpha_0^V + \beta_1^V p_i + \beta_2^V y_i + \Pi^V \mathbf{x}_i + \alpha_j^V + \nu_i^V - \mu_i^V \tag{6c}$$

However, in such instances e.g. where separate frontier functions can be argued for subsets of the day, it may still remain possible for the groups to be cross-compared. This line of intuition is the central feature/assumption lying behind the metafrontier modeling framework discussed in for example O'Donnell et al. (2008). The basic (technical) idea is that there exists some more general frontier which envelopes all of the groups, namely the metafrontier (or frontier of frontiers). This metafrontier is independent of group specific idiosyncrasies, and offers a more general concept of the best-practice frontier, or in this case the minimal energy consumption that is possible. The prevailing assumption is that there exists some concept of transferable characteristics that may attributed to any household irrespective of which group they reside.

Taking the comparison between households in cities and in villages as the reference point, it can be posited that:

- Villages generally have fewer shops than cities, and hence a smaller choice of goods. It might simply be the case that certain new and likely more energy efficient items may be harder to find in the villages than in the cities. However internet purchases do make it possible for village households to own such technologies. It then seems plausible that pure technological efficiency spillovers be achieved.

[11] A question which might be raised is why not simply model all households under a common stochastic frontier model but with groups separated by allowing price elasticities and all other parameters to differ by groups defined by k e.g.:

$$q_i = \alpha_{k0} + \beta_{k1} p_j + \beta_{k2} y_i + \Pi_k \mathbf{x}_i + \alpha_j + \nu_i + \mu_i$$

Estimating this model specification however makes some potentially inconsistent assumptions regarding the functional separation of the three groups. Specifically, in this demand function the inefficiency scores will be obtained by estimating a single variance parameter σ_μ^2, whose value will not be unique to each group (hence the inconsistency in assuming that the groups are somehow separable). Although it is true that the mean values of μ can accommodate group specific z variables.

- Relative to city households, rural residents are less likely to replace older items with new ones, which potentially are more energy efficient.

- Behavioral norms and differences may exist, and differ between the less developed villages and more developed cities. City dwellers often live at a faster pace of life, and owing to higher incomes with a higher opportunity cost of their time – the opportunity cost of being efficient may become higher, increasing the likelihood of being less efficient than possible. This suggests the possibility for behavioral features/characteristics to be transferred.

Taking the above rationale as sufficiently defensible logic for the existence of a meaningful metafrontier, it is helpful now to offer a visual characterization of the extended methodology as depicted in Figure (2). In this figure there are three individual frontiers, one each for the city, town and the village. Additionally there is a fourth frontier enveloping (from beneath) each of the group frontiers, which is the metafrontier. In this framework, each household acquires two reference points: the first is the consumption efficiency relative to the group specific frontier e.g. taking point A, given identical inputs the household could feasibly lower consumption to point A^* when benchmarking against the frontier demand for village households; the second point of reference is to benchmark against the metafrontier, from which it can be seen that for this household it is possible to realize additional efficiency improvements and reach A^{**}. At point B it is possible to see a household which is close to being perfectly efficient within its own group, but the group frontier at this point is not close the metafrontier. Conversely for point D, this household is fully efficient under both its own frontier and the metafrontier.

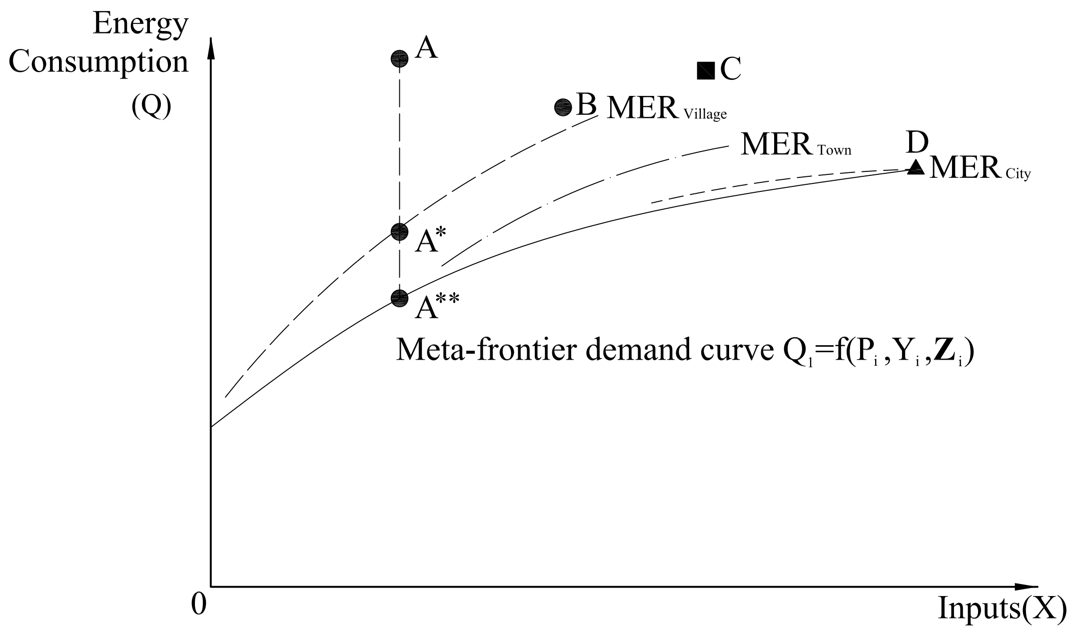

Figure 2: Illustration of a meta-frontier and group frontiers

The difference between A^* and A^{**} reflects the additional efficiency improvements only possible if the specific group is able/willing to adopt/absorb the best practices contained in the metafrontier. Their ratio is known as the meta-technical ratio (MTR) and is a useful indicator of which types of household help define the metafrontier:

$$MTR_i = \frac{TE(p_i, y_i, \mathbf{x}_i, q_i)}{TE^k(p_i, y_i, \mathbf{x}_i, q_i)} \tag{7}$$

Where $TE(p_i, y_i, \mathbf{x}_i, q_i)$ refers to the technically efficient level of energy consumption given prices, income and other household characteristics obtained from the metafrontier demand function, while $TE^k(p_i, y_i, \mathbf{x}_i, q_i)$ is in reference to the group specific frontier demand function. What remains now is to specify and outline the estimation procedure for the metafrontier demand function.

In specifying the metafrontier function, there is no a-priori reason to assume a different functional form from the group specific demand functions, with the exception that province specific effects are not included–reflecting the notion that the metafrontier should be free of any group defining characteristics. Thus the following functional form follows directly from the previous discussion:[12]

$$q_i^* = \alpha_0^* + \beta_1^* p_i + \beta_2^* y_i + \Pi^* \mathbf{x}_i \tag{8}$$

The omission of the error/efficiency terms is not accidental. The estimation procedure departs from the stochastic frontier approach, and instead optimizes (maximizes) the coefficients in Eq. (8) using linear programing methods subject to the constraint that:

$$\mathcal{D}_i \Theta^* \leq \mathcal{D}_i \Theta^k \quad \text{for all } i. \tag{9}$$

where $\mathcal{D}_i$ refers to the data matrix containing intercept(s), price, income and other household characteristics, and Θ is the stacked vector of coefficients including coefficients on the intercepts, price, income and household characteristics. It is useful to point out that the optimization problem above envelopes the estimated frontier energy consumption levels, with the effects of statistical noise in v_i and the inefficiencies in μ_i already stripped away. Or put another way that the stochastic elements of the data are already accounted for before this point.

One drawback however of the linear programing approach, which follows from the discussion above, is that because it drops the stochastic error term v_i, inference is much more problematic. Following O'Donnell et al. (2008) a bootstrap procedure, used to obtain standard errors, is applied to test the sensitivity of the metafrontier to alternative data samples, and offer something akin to conventional statistical inference. This allows some general understanding of which variables in the metafrontier demand function might be deemed statistically significant (if individual parameter bootstrap replications include zero valued coefficients), as well as offering a general indication of the overall statistical significance of the metafrontier itself (if there are no coefficients that are always different from zero). The number of bootstrap replications is set higher than strictly necessary, at B={469,000} times–one hundred times the number of village

[12]In the empirical work a common functional form is used for each group. This is not a strict requirement, but is standard practice in metafrontier applications. Were it the case that not all of the functions were identical, then a sensible choice would be to set the metafrontier function as a general function embedding each of the restricted group frontier functions.

households in the dataset.

4. Results

This section reports the main results following the estimation work. First, discussion is made of each of the separate group frontiers after which the meta-frontier results are presented. The section closes by offering a short discussion of how the results relate to the household energy ladder, and what new insights are provided.

4.1. Results of group-specific frontier demand functions

Before proceeding to discuss the specific details of the results it is noted that: (i) each of the models passes the relevant likelihood-ratio (LR) tests for the stochastic frontier model specification to be valid,[13] see Table (3), and (ii) that a series of restricted model specifications were tested for (removing groups of related variables, such as ownership of physical assets or numbers of adults/children in the household etc.), and were each rejected. Thus the reported model specifications form a suitable basis for meaningful analysis and interpretation.

Brief discussion will first be given to describing the general nature of the demand functions (highlighting key similarities and notable differences across the groups). After this, the remaining discussion will focus on the comparison of estimated efficiency scores across the groups.

4.1.1. Similarities and differences in the estimated demand functions

Table (3) reports the estimated coefficients for the demand function in Eqn. (4) separately for the city, town and village household sub-samples. Broadly speaking, for each of the three groups the signs on the estimated coefficients are as might be expected a-priori, with significant roles for economic characteristics such as income, physical household characteristics, and broader socioeconomic determinants. For example the models suggest: positive and modestly sized income elasticities; a significant and positive effect from large consumer durables (e.g. air conditioning, and refrigerators etc.); evidence that larger households (e.g. with more children/adults) consume more energy; energy consumption growing in the physical size (in terms

[13] In brief these tests ask whether a model without inefficiency terms included is 'as good' as a model with them e.g. given the model in Eqn. (4) the null hypothesis is that $\mu = 0$ and hence the efficiency related information is not necessary.

of square meters) of the property; households that use firewood consuming less electric etc. On the whole the coefficients portray a picture of energy consumption behavior that is believable and broadly consistent with features described elsewhere in the literature.

There are, as would be expected, nuances in the specific results across each of the groups. The estimated income elasticity declines as urban scale/density reduces from the city down to the village (from 0.15 to 0.11). More striking differences are observed when considering the role of key household items: taking as an example the ownership of air conditioning, with effects ranging from a 10% increase in electricity consumption in the city, to a 25% increase in towns; similarly for washing machines the increase in electricity consumption ranges from 0% in the city (noting the statically insignificant coefficient) to an increase of 18% in the town. One surprising result relates to the coefficient on TV, which is insignificant for town and village households and negative for city households. However it is worth adding that only 3% of city households do not own a TV, resulting in a high degree of collinearity between this dummy variable and the intercept term, making the results for the city households somewhat less reliable and should be taken with caution.

Larger households with more children and adults naturally create a larger amount of electricity consumption, and this is seen to be the case in all household types, though not for all sizes. More precisely, the presence of children results in no statistically significant increase in electric consumption for town households, but similarly sized impacts for village and city households. In cities it is only the first child that leads to a significant increase in energy consumption, but in villages the second child leads to further incremental growth in electric consumption–this pattern may have some connection to the enforcement of the national one-child policy which makes it relatively easier for village households to have multiple children. On the other hand the increases in electricity consumption as more adults are added to the household are generally positive and significant across the models. The other notion of household size included in the models is the physical size of the property, which broadly supports the idea that larger households in towns/cities will consume more, but larger households in the village would not. It is fair to say that village households are generally large (refer also to Table (2), often much larger than necessary since building space is less of a constraint, accordingly these houses can increase or decrease size without needing to adjust living behaviors and subsequent energy consumption patterns.

Other key results are that, on the whole, households containing one or more individuals of poor health will tend to consume more electricity, presumably on the grounds of needing to avoid excessively hot or cold temperatures inside the home and hence expending more electric for heating and/or cooling. Similarly, persons of poor health will generally be less active and spend more time indoors than someone of good health leading also to increased energy consumption. This effect is much stronger in the city, than in the villages or towns. Education (measured in terms of the highest number of years of education in the house) generally leads to lower consumption of electricity. Also, households using firewood for cooking will use less electricity. A slightly surprising result emerges for the coefficient on environmental perception, which measures whether a household believes the environmental problems to be 'severe' or not. City households are likely to be under greater pressure to reduce their energy consumption and environmental impact from the local government, reflected by a negative relationship between perceived environmental problems and electricity consumption. For village households there is a positive coefficient, but it should be recognized that village households tend to use more firewood for cooking when compared with city households, and this might therefore reflect a substitution away from firewood (and coal) to less polluting electricity.

Table 3: **Estimated Coefficients for the frontier demand functions.**

	Ordinary least squares			Stochastic frontier analysis		
Main Variable	City	Town	Village	City	Town	Village
Income Elasticity	0.16^{***}	0.13^{***}	0.11^{***}	0.15^{***}	0.12^{***}	0.11^{***}
Automobile	0.05	-0.05	0.13^{***}	0.05	-0.04	0.13^{***}
Air Condition	0.11^{**}	0.25^{***}	0.20^{***}	0.10^{**}	0.25^{***}	0.20^{***}
TV	-0.17^{**}	0.20^{*}	0.06	-0.18^{**}	0.16	0.07
Mobile	0.06	0.04	-0.00	0.06	0.02	0.002
Fridge	0.31^{***}	0.27^{***}	0.26^{***}	0.30^{***}	0.27^{***}	0.26^{***}
PC	0.16^{***}	0.22^{***}	0.16^{***}	0.14^{***}	0.22^{***}	0.16^{***}
E-bike	0.04	0.10^{**}	0.07^{***}	0.04	0.07^{*}	0.07^{***}
Washing Machine	0.06	0.18^{***}	0.15^{***}	0.06	0.18^{***}	0.15^{***}
Motorcycle	-0.01	0.00	0.02	0.01	-0.02	0.02
1 Child	0.07^{**}	0.03	0.07^{***}	0.07^{**}	0.03	0.07^{***}
2 Children	0.10	0.06	0.10^{***}	0.08	0.07	0.10^{***}
3 and more Children	0.35	0.01	0.01	0.32	0.03	0.003
2 Adults	0.07	0.05	0.07^{**}	0.08^{*}	0.06	0.08^{**}
3 Adults	0.11^{**}	0.21^{***}	0.08^{*}	0.15^{***}	0.21^{***}	0.10^{**}
4 Adults	0.16^{**}	0.16^{**}	0.14^{***}	0.21^{***}	0.16^{**}	0.16^{***}
5 and more Adults	0.27^{**}	0.13	0.15^{***}	0.32^{***}	0.14	0.17^{***}
Health Poor	0.07^{**}	0.08^{**}	0.04^{*}	0.39^{***}	0.19^{***}	0.03^{*}
House Size	0.002^{***}	0.001^{**}	0.00^{*}	0.002^{***}	0.001^{**}	0.00
Apartment	0.08^{**}	-0.05	0.08	0.08^{**}	-0.05	0.08
Water Source	-0.10	-0.01	0.00	-0.09	0.02	0.06^{***}
Energy Source	-0.79^{***}	-0.29^{***}	-0.31^{***}	-0.31^{*}	-0.21^{***}	-0.33^{***}
North	-0.14	0.07	0.25^{***}	-0.14	0.04	0.25^{***}
Local Economy	-0.02	-0.01	0.02	-0.03	-0.01	0.02
Local Cleanliness	0.01	0.08^{***}	0.01	0.01	0.08^{***}	0.01
Social Homogeneity	-0.01	0.01	-0.02^{*}	-0.01	0.01	-0.01
Financial Assets	-0.01	-0.01	-0.01^{***}	0.17^{***}	0.01	0.004
Environmental Perception	0.01	-0.00	0.02^{***}	-0.03^{***}	0.01	0.01^{***}
Max Education Year	-0.00	-0.00	-0.01^{*}	-0.01^{*}	-0.01	-0.01^{***}
Intercept	2.83^{***}	2.35^{***}	2.48^{***}	1.00^{***}	2.33^{***}	2.18^{***}
N	1366	1046	4692	1366	1046	4690
LR test	-	-	-	Pass	Pass	Pass
Log likelihood value	-1054.73	-854.29	-4383.73	-1039	-839	-4365
Mean efficiency	-	-	-	0.651	0.899	0.84

Notes: (1) Superscript stars denote significance at the following respective levels: *** = 1%, ** = 5% and * = 10%; (2) additional dummies are included in the model, but not reported, for (i) the industry which the head of household works in and (ii) province specific fixed effects; (3) The figures in the parentheses are standard errors; (4) The variable *House size* is measured in levels, and not in natural logarithms.

4.1.2. Efficiency score analysis

The average electricity consumption efficiency scores are reported at the bottom of Table (3). City, town and village households are respectively 0.65, 0.90 and 0.84 efficient in electricity consumption with respect to households of the same type. One must exercise caution in comparing these values against eachother, since they are obtained from assumed separable demand frontiers–formal comparisons must instead be made relative to the metafrontier and are done below. Nonetheless one cannot help but notice the stark difference in the average level of efficiency seen in city households relative to the others–which is highly indicative of a fundamentally different distribution of efficiency scores within the city group–brings immediate question to the notion of the household energy ladder. This result, if it holds with respect to the metafrontier also gives a strong indication that the relatively wealthier city households, who implicitly have access to more efficient technologies, are at the same time much less efficient in their consumption of electricity, from which it follows that having more efficient appliances does not perfectly correlate with consumption efficiency.

This potentially gives rise to one of the first policy implications of the paper, that there exists a potential empirical trade-off between technological efficiency (acquired through wealth) and consumption efficiency. Such a trade-off might even be rational if one takes into account the subjective value (opportunity cost) of time spent being efficient, which is increasing in income. However, a direct comparison of the TE scores is of limited value since it only compares a household to the group specific frontier, a more careful comparison requires an evaluation of the group to the metafrontier, therefore this policy implication will be re-evaluated once the metafrontier results are presented.

4.1.3. The determinants of efficiency

Attention is now focused towards the variables used to describe the distribution of efficiency, i.e. the Z variables in the stochastic frontier efficiency effects model. Estimation results are reported in Table (4). [14] The principal aims here are to demonstrate that at least some of the variables are significant, implying a meaningful economic identification of the level of efficiency, and also that there are differences across the three groups, serving as additional support that the separation of the sample was justifiable. In short, both goals are achieved.

[14]OLS results serve as a useful comparison and for this reason are also shown in Table (4), however from a conceptual perspective, OLS estimates do not explicitly model efficiency and are not therefore fully compatible with the underlying economic modeling approach. OLS results can be used within two step estimation procedures such as modified OLS or corrected OLS to produce efficiency-like measures, however as discussed in Kumbhakar and Lovell. (2003), each of these methods have their shortcomings relative to SFA. Additionally, the likelihood ratio tests in Table (4) show that SFA should not be rejected in favor of OLS, thus it is of limited interest to offer deeper discussion of the OLS results.

Several variables appear in both the demand function and efficiency mean equation, such as the environmental perception indicator, variables describing the likelihood of power failure and other variables. These variables are likely to influence both energy demand and efficiency term. In the efficiency effects equation only the education of the head of household is accounted for on the premise that she/he will be responsible for purchasing decisions that will set the boundary of the efficient point.

Table 4: **Estimated Coefficients for the efficiency effects equations of the group specific frontiers.**

Efficiency Variable	City (SFA)	Std.Error	Town (SFA)	Std.Error	Village (SFA)	Std.Error
Environmental Perception	0.05***	(0.003)	-0.02*	(0.01)	-0.09	(0.10)
Power Failure Sometimes	0.03***	(0.003)	-0.02	(0.04)	1.96**	(2.73)
Power Failure Often	-0.09***	(0.01)	0.33***	(0.13)	3.77	(2.73)
Poor Health	-0.39***	(0.02)	-0.188**	(0.05)	0.37	(0.70)
Financial Assets	-0.19***	(0.01)	0.01*	(0.007)	-1.66***	(0.40)
Primary School	0.08***	(0.01)	0.12	(0.09)	0.94	(0.79)
Junior School	0.09***	(0.02)	0.23	(0.09)	1.10	(1.24)
High School	0.18***	(0.01)	0.35***	(0.11)	8.00***	(3.19)
College	0.12***	(0.02)	0.10	(0.12)	15.46***	(4.53)
University	0.22***	(0.03)	-0.34**	(0.16)	1.37	(15.03)
Energy Source	-2.51***	(0.16)	-1.43***	(0.44)	0.40***	(0.78)
Water Source	-0.08***	(0.01)	-0.04	(0.10)	-9.76***	(3.27)
Efficiency Intercept	1.96***	(0.07)	-0.03	(0.07)	-19.65***	(6.73)
sigmaSq	0.27***	(0.01)	0.29***	(0.01)	6.39***	(1.65)
gamma	0.00	(0.00)	0.00***	(0.00)	0.95***	(0.01)

Notes: (1) Superscript stars denote significance at the following respective levels: *** = 1%, ** = 5% and * = 10%; (2) The figures in the parentheses are standard errors.

Across the columns in Table (4) it can be seen that most variables are significant, implying that they help to place a meaningful value on the household level of efficiency. Further, across the columns some important differences emerge. For instance, higher educational attainments by the head will result in a lower energy efficiency (albeit with very different magnitudes of effect between cities, towns and households),[15] until the point of attaining a university degree, where the effect becomes positive (with a coefficient of -0.34) for the town group. Generally speaking experiencing a 'Power Failure Sometimes' results in a lower level of consumption efficiency for city and village households. For households that use some firewood within their household energy mix (reflected by the variable 'Energy Source') there are differing results

[15]The fact that improved education coincides with greater inefficiency may stem from the increased number and diversity of activities that occur in better educated households, which create more opportunities for inefficient behaviors.

across the three groups. For village households, if firewood is the main energy source for cooking (which remains quite common in villages), energy efficiency goes down. On the contrary, efficiency increases for the other two groups. This suggests different lifestyles between the rural and non-rural households.

Table 5: **Energy Consumption Efficiency Distribution of the Group Frontiers for City, Town and Village Households**

	City		*Town*		*Village*	
Percentile	%	Cumulative %	%	Cumulative %	%	Cumulative %
0-0.99	3.9	3.9	-	-	-	-
10-19.99	3.1	7.0	-	-	0.04	0.04
20-29.99	2.2	9.2	-	-	0.06	0.1
30-39.99	8.1	17.3	-	-	-	0.1
40-49.99	10.3	27.6	0.1	0.1	0.3	0.4
50-59.99	13.4	41.0	0.7	0.8	0.6	1.0
60-69.99	14.6	55.6	2.6	3.4	2.3	3.3
70-79.99	12.4	68.0	16.3	19.7	14.6	17.9
80-89.99	10.8	78.8	25.1	44.8	77.2	95.1
90-99.99	19.9	98.7	55.2	100	4.9	100
100	1.3	100	-	100	-	100

Notes: (1) Range value is the ranges of energy efficiency scores of households in city, town and village; (2)'%' and 'Accumulated %' are the household percentage and accumulated percentage within each Range Valuse for different household types, respectively.

Table (5) summarizes the obtained efficiency scores and their distributions across cities, towns and villages. From this it can be seen that city households have the largest range of efficiency, with just over 9% of households being below 30% efficient–a large enough portion to be considered more than just outliers to be removed from estimation. Both city and village households have few observations with less than 60% efficiency, with many households being more than 80% efficient.

4.2. *Metafrontier results*

For the metafrontier results, several features will be discussed in the following order: first, as with the group frontiers, a general look at the nature of the metafrontier demand function will be provided; following this, attention will be turned to discussion of the meta-technical efficiency; lastly, a summary will be made of the determinants of meta-technical efficiency, comparing against the determinants of the group specific frontiers.

Table 6: **Metafrontier coefficients and their confidence intervals.**

	Coefficient	Lower-bound	Upper-bound	Percentage
Income Elasticity	0.12***	0.06	0.13	1.00
House Size	0.00	0.00	0.00	0.34
Automobile	0.04	0.00	0.16	0.42
Air Condition	0.19***	0.09	0.24	1.00
TV	0.09	0.00	0.11	0.62
Mobile	0.00	0.00	0.05	0.24
Fridge	0.34***	0.20	0.36	1.00
PC	0.04***	0.07	0.21	1.00
E-bike	0.10	0.00	0.12	0.85
Washing Machine	0.10***	0.12	0.10	1.00
Motorcycle	0.03	0.00	0.06	0.53
Financial Assets	0.14***	0.12	0.14	1.00
Health Poor	0.04***	0.03	0.15	1.00
1 Child	0.08***	0.02	0.16	1.00
2 Children	0.13***	0.04	0.19	1.00
3 Children and more	0.00	0.00	0.16	0.18
2 Adults	0.00	0.00	0.13	0.65
3 Adults	0.11	0.00	0.16	0.98
4 Adults	0.06***	0.04	0.21	1.00
5 Adults and more	0.04	0.00	0.21	0.97
Apartment	0.00	0.00	0.11	0.40
Water Source	0.16***	0.03	0.13	1.00
Energy Source	0.00	0.00	0.00	0.00
Local Economy	0.00	0.00	0.02	0.27
Local Cleanliness	0.01	0.00	0.01	0.24
Social Homogeneity	0.00	0.00	0.01	0.10
Environmental Perception	0.00	0.00	0.65	0.06
North	0.00	0.13	0.25	1.00
Max Education Year	0.00	0.00	0.01	0.21
Intercept	0.06***	0.14	1.92	1.00
N	7,102			
mean efficiency	0.628			
Mean Technology Gap	0.372			

Notes: (1) The lower/upper bound is under the 95% confidence interval; (2) Percentage represent the percentage of possitive coefficiencts (bigger than 0) of the total 469,000 times bootstrap; (3) Additional dummies are included in the model, but not reported, for the industry which the head of household works in; (4)Coefficient significant: variables with the possitive lower bound ***.

4.2.1. The metafrontier demand function: Variable significance.

As with discussion of the group frontiers, it is first important to establish the general nature of the metafrontier, and that it is roughly in line with a-priori expectations. Table (6) reports results from the linear-program for the metafrontier and provides key information relating to the components describing the metafrontier demand function. The Table includes the coefficients, obtained via linear programing using the original sample, as well as estimates of the sampling variability via a bootstrap estimation procedure. The 'lower-' and 'upper-bound' columns describe the lower 2.5% and upper 97.5% points of the empirical coefficient distributions. If this range does not include zero, then the coefficient is deemed significant. The final column records the percentage of individual replications where the coefficient was not equal to zero: a higher value here suggests a higher possibility of impact from a particular variable on energy demand. This is interesting for variables such as the ownership of an electric bike, which has a non-zero effect 85% of the time.

A number of variable groups contain significant coefficients: Income has a positive, though again relatively small in size elasticity; ownership of key household assets including fridge, PC, washing machine lead to increases in electricity consumption; households with greater financial assets tend to consume more; presence of someone of poor health in the household correlates with a higher electricity consumption; and households with more children/adults will have higher consumption. These results are (i) generally consistent with the group specific demand functions, which would be generally expected if the metafrontier is to be considered a reasonable generalization of the group specific frontiers and (ii) the coefficients are generally plausible in sign and size.

4.2.2. Efficiency with respect to the metafrontier

With a view of the existence and stability of the metafrontier established[16] attention can be reasonably turned towards understanding the distribution of efficiency with respect to it.

[16] As yet there is no formal econometric test of the existence of a metafrontier, but parameter significance alongside plausible results are an indicator of sorts that.

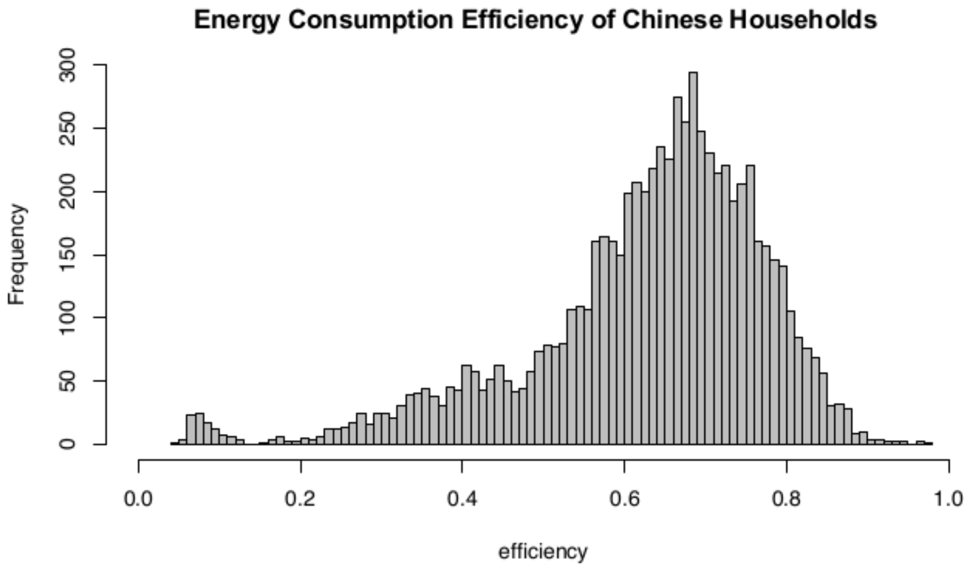

Figure 3: Energy Consumption Efficiency Distribution of the Meta-frontier for Chinese Households

Figure (3) plots the distribution of meta-technical efficiency for the full sample of households. The average efficiency across the sample is 0.63, which is substantially lower than a simple weighted average of 0.81 across the group frontiers obtained using the results in Table (3). The difference between these two numbers is a reflection of the fact that many households are operating at a point above their own group demand curves that is not tangent to the metafrontier. This can be noted by referring back to Figure (1) and seeing that for each of the group frontiers there is only part of the curve that is tangent to the metafrontier, and this is the only 'technically efficient' allocation for this group.

Figure (4) provides deeper inspection by looking at the meta-technical efficiency scores for each of the three household types. Town and villages prove to have similar mean efficiency scores at 0.653 and 0.652 respectively, while the city households continue to have the lowest efficiency at 0.529. As per the group specific results, the city households still reflects a cluster of highly inefficient households, though the large majority of observations lie between 40-80% efficient.

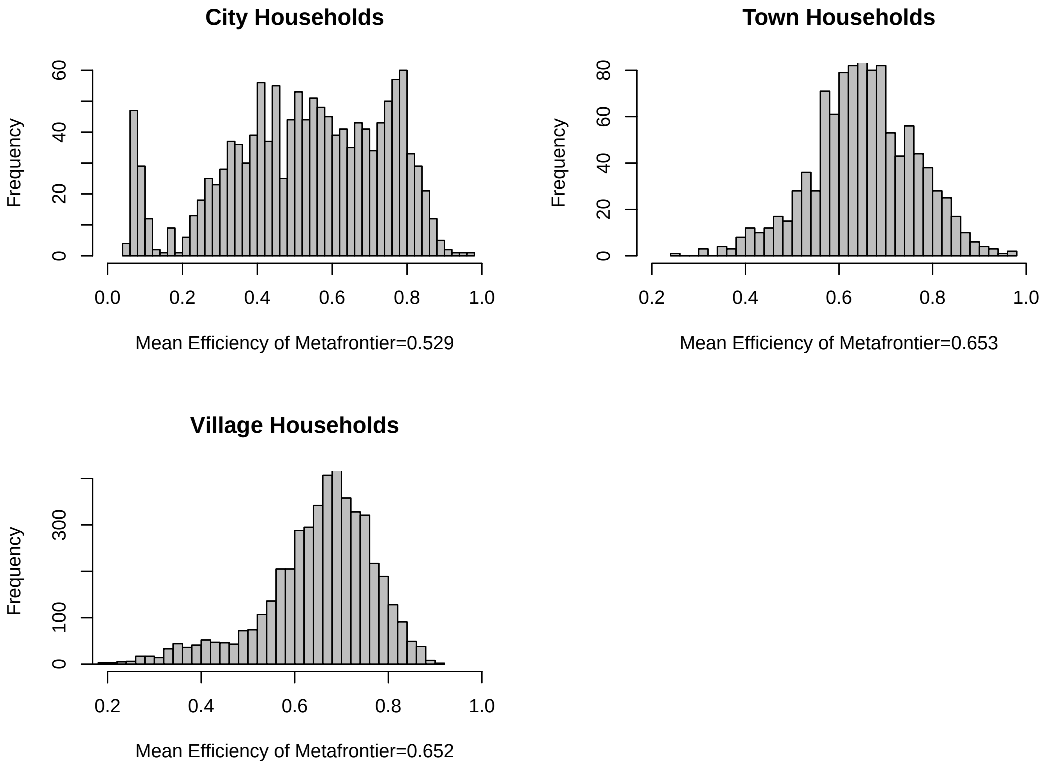

Figure 4: Energy Consumption Efficiency Distribution of the Metafrontier for City, Town and Village Households

4.2.3. The determinants of meta-technical efficiency

The linear program used to obtain the metafrontier does not allow direct inclusion of efficiency effects variables e.g. the variables used to describe the mean inefficiency.[17] However, wishing to still understand the extent to which the observed efficiency scores are influenced by other variables the following regression model is estimated:

$$\left(1 - \widehat{MTE}_i\right) = \mathbf{\Gamma}_1 \mathbf{z}_i + \varepsilon_i \tag{10}$$

The term on the left hand side, $\left(1 - \widehat{MTE}_i\right)$, is a measure of inefficiency, this transformation is needed to ensure comparability with the determinants of efficiency for the group specific frontiers. On the right hand side of the equation the vector $\mathbf{z}_i$ contains the same set of variables as in the case of the group specific results. OLS is used in the first instance to estimate this

[17] In principal a stochastic frontier model could be used in place of the linear program, allowing efficiency effects to be modeled simultaneously. This however comes at the expense of using a method that does not guarantee an envelope around the data points.

equation, but noting that $\widehat{MTE}_i$ is not perfectly normally distributed a robust regression is used to support inference. Similarly the data generating process is truncated at zero and one, so a third alternative TOBIT specification is also estimated for comparison. The results across these three models are very similar–see Table (7).

Table 7: **Estimated Coefficients for the efficiency effects equations of the metafrontier.**

Efficiency Variables	OLS	Std. Error	Robust OLS	Std. Error	Tobit	Std. Error
Environmental Perception	0.004***	(0.0005)	0.003***	(0.0004)	0.004***	(0.0005)
Power Failer Sometimes	0.009***	(0.002)	0.01***	(0.002)	0.009***	(0.002)
Power Failer Often	0.03***	(0.006)	0.03***	(0.005)	0.03***	(0.006)
Poor Health	-0.03***	(0.002)	-0.02***	(0.002)	-0.03***	(0.002)
Financial Assets	-0.04***	(0.0003)	-0.04***	(0.0003)	-0.04***	(0.0003)
Primary School	-0.001	(0.003)	-0.001	(0.003)	-0.001	(0.003)
Junior School	0.004	(0.003)	0.00	(0.003)	0.004	(0.003)
High School	0.06***	(0.004)	0.05***	(0.003)	0.06***	(0.004)
College	0.02***	(0.005)	0.02***	(0.005)	0.02***	(0.005)
University	0.06***	(0.007)	0.07***	(0.006)	0.06***	(0.007)
Energy Source	-0.06***	(0.002)	-0.05***	(0.004)	-0.06***	(0.002)
Water Source	-0.07***	(0.002)	-0.06***	(0.002)	-0.07***	(0.002)
Intercept	0.73	(0.005)	0.30	(0.004)	0.73	(0.005)
N	7,102		7,102		7,102	
R-sqr	0.68		0.68			
Log likelihood	7,560.67		7,493.54		7,561	

Notes: (1) Superscript stars denote significance at the following respective levels: *** = 1%, ** = 5% and * = 10%; (2) The figures in the parentheses are standard errors.

Across the columns in Table (7) it can be seen that most variables are significant, which was also the case with the group-specific frontiers. Similar patterns emerge as were seen for the group specific models. For instance, higher educational attainments by the head will result in a lower energy efficiency. Generally speaking experiencing a 'Power Failure Sometimes' leads to lower efficiency. Use of energy sources other than electricity within the household results in a higher efficiency of electricity consumption.

4.3. The champions of efficiency and the household energy ladder.

From the empirical results it is possible to develop a picture of the champions, and laggards, of electricity consumption efficiency. Ordering the meta-technical efficiency scores from the lowest to the highest, the champions will be defined by the top 5% most efficient households, and the laggards as the bottom 5%. The simple question being posed of these households is then what group they belong to, city, town or village households. Recalling from the descriptive statistics in Table (2) that this typology loosely aligns with the level of household income e.g. city is wealthiest, then town and lastly village the poorest type of household. Thus, this enables to ask the question ‘are the wealthiest households the most efficient?’

From the literature review, and general discussion on the concept of the household energy ladder, it is expected that these households can purchase the best technologies and be most efficient. The existing literature does not however say much regarding whether these households will in fact be the most efficient in their use of the more efficient appliances. As mentioned, the work here does not challenge the notion that wealthier households get better access to new technologies, but focuses on this latter issue of relative consumption efficiency.

Table (8) reveals that the champions of efficiency are not city households. Of the top 5% most efficient households, only 22% are from cities, while the remaining 78% come from towns (20.6%) and villages (57.4%). Village households can claim the title of being the champions of efficiency. Conversely city households can claim losers rights, with more than 71% of the least efficient households being from cities.

Table 8: **The champions of efficiency: this table shows the shares of city, town and village households in the top (and bottom) 5% most (least) efficient** observations.

Meta-technical efficiency	City	Town	Village
Top 5%	22.0%	20.6%	57.4%
Bottom 5%	71.5%	1.12%	27.3%

From the above, one might attempt to craft out a refined or extended hypothesis/definition regarding the energy ladder concept which posits that households with greater wealth are generally able to achieve greater access to more energy efficient appliances (this is the original postulate), however along with this wealth appears to come an inherent tendency to be less efficient in consumption of electricity. The implications of this for policy are therefore that city households may be for example the most important candidates for energy education and wider energy policy, since they appear to lack either (i) an understanding of how to use their goods efficiently and/or (ii) a desire to do so. Seeing as these households each consume a much higher level of electricity, and also that urbanization rates continue at a high level–thereby increasing the number of city households in the future substantially–this would appear to have the potential to reduce large amounts of energy consumption. On the other end of the spectrum, village households are much more likely to be efficient, but evidently lack the resources to obtain the best technologies–it is likely for these households that subsidy programs to purchase better technologies or to provide direct energy assistance schemes may be more suitable than efficiency education programs.

However in closing it should be recalled that although the conclusions presented above are plausible, they are nonetheless based on a single sample, and therefore should be researched in a more focused fashion using data across multiple waves, and from other countries for comparison.

5. Concluding remarks

This paper provides a novel attempt to quantify energy consumption efficiency at the level of the household. The empirical work is done using a unique cross-section of data for more than 7,000 Chinese households in 2012. What is illustrated is a staggering level of inefficiency in electricity consumption. The results suggest that households are on average around 63% efficient, and therefore that there exists huge potential to reduce electricity consumption. Improvements in the efficiency of energy consumption offer additional co-benefits of emission reduction and hence reduced environmental problems. Thus, given the identified scale of inefficiency, and the urgency to manage environmental problems, it would seem that additional policies aimed specifically towards household energy efficiency management could be of strategic importance. This conclusion is not confined to the case of China, and is fully expected to generalize to all other economies.

Important differences in the nature of energy demand and efficiency levels are documented across city, town and village households. Among other things, these differences bring into question the conventional understanding of the household energy ladder concept. To elaborate, the energy ladder concept implies that wealthier households have access to more efficient technologies than poorer households, and hence can be more efficient. The results here partially reinforce this sentiment by showing the richest households (i.e. the city households) to be the group that defines the metafrontier best practice technology. However the results also highlight that these households have by far the lowest average consumption efficiency. This is a feature not yet reflected within the existing literature discussing the household energy ladder. It could be argued that existing concepts of the household energy ladder are therefore incomplete, and should not be used as a motivation for giving less policy attention to wealthier households. In economic terms this might be considered a market failure problem insofar as wealthy households should be able to do better, but in practice they fail to achieve the best outcomes by themselves.

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