Environmental Science and Pollution Research (2023) 30:70386–70396
https://doi.org/10.1007/s11356-023-26731-w

RESEARCH ARTICLE

Impact of financial decentralization on energy poverty and energy demand tendencies in Chinese settings

Jianhe Wang[1] · Ziman Xiang[2] · Xiaohan Jiang[3] · Lei Wang[4] · Lei Chang[5]

Received: 12 November 2022 / Accepted: 27 March 2023 / Published online: 6 May 2023

Abstract
This study intends to test the connection between fiscal decentralization, energy demand dynamics, and energy poverty status from the context of China. The study has collected large datasets ranging from 2001 to 2019 to justify the empirical findings. The long-run analysis economic techniques were considered and applied for this. The results indicated that a 1% adverse change in energy demand dynamics causes 13% of energy poverty. Supportively, a 1% positive rise in energy supply to fulfill energy demand reduces energy poverty by 9.4% in the study context. Moreover, empirical findings show that a 7% rise in fiscal decentralization accelerates 19% fulfillment in energy demand and mitigates energy poverty up to 10.5%. We demonstrate that if enterprises can only alter their technology choices in the long run, the short-run reaction of energy demand must be less than the long-run response. Second, we demonstrate that the elasticity of demand approaches its long-run level exponentially at the rate defined by the capital depreciation rate and the economy's growth rate, using a putty-clay model with induced technical development. According to the model, it takes more than 8 years for half of the long-run impact of induced technological change on energy consumption to be realized in industrialized nations once the carbon price is implemented. This research document also gives multiple policy directions for policy developers.

Keywords Energy demand dynamics · Energy poverty · Energy efficiency · Energy supply disruptions · China

Introduction

Reduced power use and a shift to carbon-free energy sources are two ways a levy on carbon cuts emissions (Alemzero et al. 2021). The second route is based on the premise that a carbon tax raises the energy price, encouraging people and businesses to use less (Li et al. 2021a). This research considers what causes the decrease in energy use (Iqbal et al. 2021a). The electricity consumption route will be critical in the early nineteenth century of a low-carbon shift. The carbon price will have little impact on energy prices and consumption after minimal technologies dominate energy production. In contrast, as fossil fuels account for 81% of the global power sector, a carbon price would significantly influence energy prices (Li et al. 2021b). As a result of the price rise, we may anticipate less energy being used (Anh Tu et al. 2021). However, the amount and timeliness of demand's reaction to changes in price are also a mystery at this point. For an accurate evaluation of the success of a carbon tax in reducing CO2 emissions, especially in the early stages of a low-carbon shift, it is critical to understand this reaction (Iqbal et al. 2021b).

Responsible Editor: Nicholas Apergis

✉ Lei Chang
chang06@mail.ustc.edu.cn

Jianhe Wang
2101060725@cupl.edu.cn

Ziman Xiang
popo@mail.ccom.edu.cn

Xiaohan Jiang
3220200253@bit.edu.cn

Lei Wang
wangleiaixuexi@163.com

[1] Business School, China University of Political Science and Law, Beijing 100088, China

[2] Central Conservatory of Music, Beijing 100031, China

[3] School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China

[4] School of Economics and Management, Beijing Forestry University, Beijing 100083, China

[5] School of Economics, Peking University, Beijing 100871, China

Two factors influence how consumers react to an increase in price: supply and demand. The first and most obvious result is that energy is being replaced by other production variables (Ahmad et al. 2021). For example, companies might substitute labor for power, or customers could opt for more energy-efficient public transportation over other options (Iqbal and Bilal 2021). The current economic system, which cannot be changed soon, restricts the available substitute options. The second consequence is linked to long-term alterations in the financial system (Tehreem et al. 2020). A better term for this phenomenon is "cost-inducement of innovation." The modernization and extension of public transportation networks, for example, encourage commuters to use them instead of cars by developing and adopting more energy-efficient manufacturing techniques (Tiep et al. 2021).

Technological change and its influence on energy demand must be taken into account by legislators as well (Sun et al. 2020). Carbon taxes could be needed in conjunction with measures encouraging the widespread adoption of nil energy sources if energy consumption decreases over the long term due to higher pricing (Sun et al. 2020). Energy demand change will be evaluated for the past and future based on how quickly it reaches its long-term level. Xu et al. (2020) agree with this point of view, noting that further research into the dynamics of energy-saving technology evolution is required to augment the current body of knowledge.

The essay makes three contributions to the body of knowledge. First, we show that in an overall situation, a strong firm's long-term response to energy demand must be greater than its short-term reaction (Iram et al. 2021). Equivalently, suppose energy costs rise as a result of technical development. In that case, the improvement (i.e., an increase in energy demand) will be less and will not be as significant (Baloch et al. 2020). As a follow-up, we demonstrate that when enterprises are unable to change their technology choices to account for vintages of successfully installed capital, energy demand approaches its long-run level (Agyekum et al. 2021), which is at a pace that is exponentially proportional to the sum of equity decay rates and economic growth rates (Iqbal et al. 2021a). In the third place, we look at the long-term influence on macroeconomic factors like GDP, employment, and salaries of long-term technological adjustments linked to energy efficiency (Zhang et al. 2021). In Poland, the simulated findings show that a carbon price reduces GDP when companies modify their equipment. This process, however, also contributes to a further decline in the demand for mining sector production and increases the downward pressure on employment in this industry (Xu et al. 2020).

Using numerical multi-sector simulations, we arrive at the third conclusion about the macroeconomic effects of long-term effects on energy demand. For this, the dynamic stochastic general equilibrium model is built on the aforementioned analytical framework. Input–output matrices for the Polish economy were used to calibrate the model, and an objective case analysis was conducted for Poland. The model considers the effects of price changes on general equilibrium, demand movements across 11 different economic sectors, and carbon emissions (Li et al. 2021c). Researchers studying climate policy (or resource scarcity) have looked at the dynamic trajectory of technological progress. The DTC method differs from the technological frontiers paradigm in this article (Chien et al. 2021). According to the study's predictions, even countries that are not technologically frontier or do not have an extensive R&D industry would see an adjustment in their technology due to a local carbon price. Second, technology can respond even if the economy grows at a zero percent annual pace (Mohsin et al. 2021a). We can model in a computable general equilibrium and dynamic stochastic general equilibrium setting without requiring monopoly status, which we accomplish in the second part of the study.

As a basis for future academic research and the development and evaluation of successful programs in cold or warm climates, understanding the phenomena of energy poverty (EP) among families calls for standardization of definitions and measurements. In developing nations, where the problem and notions of EP vary significantly from the emergence of EP in Europe and America, the meaning and assessment of EP impact findings about its prevalence, policy target, and evaluations of government efficacy.

Literature review

EP was defined as the failure to pay for adequate heating at home by Bradshaw and Hutton (1983), extending newly declassified work directed (Mohsin et al. 2021b), which developed the concept, focusing on disproportionally large energy consumption by low-income families as the basis for concluding. Increased discussion on impression measures and how they relate to the more known spending-based indicators was encouraged by comparisons of EP spending across countries, such as EU member states. Li et al. (2021a) conducted significant research in the UK comparing an expenditure-based measure with a perspective one. They found substantial disparities between families who were 10% power deprived and those who believed they could not afford energy (Anser et al. 2020). To boost responsiveness and stability, we examined data from three twice as many homes as previous studies had almost 20 times quite so much data. BEIS confirms that in China, the overlap between measures perception and those depending on spending is still minimal (Alemzero et al. 2021).

This eliminates the possibility that distinctions between metrics reflect sample selection distinctions, elements in mind, and unobservable character traits of families. Regressions were utilized to analyze household factors linked with the relationship between the perceived and proXy EP indicators when comparing European EP rates (Yousaf et al. 2020). Loss of the ability to provide proper warmth' is a factor in research (Mohsin et al. 2021a). There is a larger argument regarding the optimal technique to quantify EP in homes, and both publications add to that discussion (Xian et al. 2020). Energy affordability (EP) measurements may be divided into two categories. One of these research shows self-reports of the lived experience and study indicators, including their measurements. And on the other hand, they suggest that you do not concentrate too much on one EP measure or criteria (Yuan et al. 2021).

On the surface, technological valuation change should behave similarly to substitutability, encouraging companies to further reduce costs on an input that had previously been relatively cheap (Nussbaumer et al. 2012). Previous studies show graphically that a rise in the price of a filthy input reduces demand compared to other information, as demonstrated by technological progress (Nussbaumer et al. 2012). However, because of the former, the impact of induced technical change on determined broadly may vary from the effect on relative demand. Even if caused technological progress reduces the amount of filthy input required to produce one unit of output (Pachauri et al. 2004), it also lowers the output cost, which supports a rise in the demand for production (Barnes et al. 2011). No evidence can be found of how caused technical development affects overall energy consumption in the long run. Several models of energy-saving knowledge stock indicate a net negative effect (Bouzarovski et al. 2012).

The study findings indicate previous findings while allowing for subtleties to be detected and expanded thanks to the dataset utilized in this investigation, which is explained in more depth below (Kaygusuz 2011). The data included in this study was described in more detail below (Bhide and Monroy 2011). There have been fluctuating energy prices throughout studies. Thus, we can establish that the absence of overlap amongst EP variables is not a passing trend (Bednar and Reames 2020). This is the first study to use the EP to examine (Thomson et al. 2017a). A topic on the cost of heat is missing from the more current knowing social collection. Therefore, a comparable analysis for the UK cannot be performed for far more recent times (Herrero 2017). Nevertheless, as we will see later, further data suggest that the conclusions are still valuable and generally relevant (Sagar 2005).

The first conclusion may be drawn from applying the principle to energy consumption (Day et al. 2016). Samuelson was the first to propose this idea. It says that in an unfettered economy, demand for any input will respond to a change in pricing more strongly than in a limited one (Papada and Kaliampakos 2016). The idea is predicated only on the premise that the business is profitable and competitive. An analytic modeling approach combining information from the putty-clay vintage model and the technological border paradigm yields the second finding, which deals with system dynamics (Okushima 2016). Using the spackle paradigm, we suppose a company must decide on the additional capital required and its energy efficiency when installing a new vintage (Halff et al. 2014). After the vintage is placed, the company cannot reverse its choice (Adusah-Poku and Takeuchi 2019).

Furthermore, we presume the company can select a technique during antique installation. I am reading the material on the cutting edge of technology (Meyer et al. 2018). The company must choose an energy-intensive, capital-saving innovation and an energy-saving and capital-intensive technology since their productivity metrics vary (Thomson et al. 2017b). There are also cases when the company can only pick the technologies for one vintage and stick with them (Culver 2017). This goes against the grain of what has traditionally been assumed in the literature (Sareen et al. 2020).

Data and methodology

Data for the study

For this study, yearly data was collected to empirically assess the nexus between the study variables. It includes the years from 2001 to 2019 and represents the Chinese context. About 4771 new energy generation powerhouses were constructed in the last 5 years to meet energy generation and effectively combine with energy poverty mitigation. Our study started in 2001–2019 to correspond with the launch of the Italia context boosting group to simplify the interpretation of data, particularly in terms of temporal energy demand trends and energy poverty identification.

Frame interpolation homes from devolved administrations occur when booster samples are included, leading to a rise in the number of people reporting that they have EP. As a result of previous smaller average incomes (Wales and Northern Ireland) and smaller gas infrastructure, families in the regional assemblies (Scottish and Ireland) are at higher risk of EP. To understand better how EP symptoms vary, we analyzed this skewed survey instead of calculating the frequency of EP in the general public.

Context of study and conceptualization

Every necessary factor, such as those required to compute the four EP measures, must be provided in at least one survey wave for a family to be considered for the study. Between 2001-2002 and 2008-2009, an imbalanced sample of 55,772 observations was collected from 10,465 homes. From 2001–2012 to 2012–2018, the two expenditure-based metrics (10% EP and LIHC EP). The management, on the other hand, as previously said, is where a home is situated. Although the association between household gross annual income, EP, and yearly housing costs (net of housing benefit) and EDD is also investigated, as stated following, examining a comparable relationship utilizing outlay indicators is neither relevant nor useful. The consumer price index translated all currency values to 2008 dollars. As a safety net, the multiple regression incorporates survey wave dummies and monthly poll variables representing the year the study was conducted.

After accounting for additional covariates and temporal lags, logit methods can determine the relationships between the abovementioned households and each EP signal. If family I am resource deprived during period t, and the variable y_{it} has a value of 1; otherwise, it has a value of 0. Outlay metrics produced here vary from official English statistics in two areas, notably their use of reporting rather than modeled EP and annual profit instead of gross pay net all taxation. However, this EP-modeled factor is not accessible for our comparison experiment. Therefore, we cannot use it to determine the principal dwelling area. Since recorded EP may underestimate EP if the poorest families limit their EP, it is preferable to utilize modeled EP. Inadequate is not a ubiquitous problem, according to Deller and Waddams (2018), who found that EP rates in Britain are more excellent when using reported rather than modeled EP. Furthermore, using actual (rather than simulated) spending has certain benefits since it is more in line with particular families' substantial experience in the industry. This metric appeared to be a better indication of the family's income inability to buy proper heating than just not being able to remain warm enough. It was the same with the measurement of insufficient warming capabilities, which we felt was inappropriate since it lacked the crucial affordability component.

Empirical measurement and analysis

External characteristics such as the age of family size, the presence of kids, the amount of immediate relatives, and whether a piped gas linkage is present are all considered when looking at household characteristics associated with EP indicators. The Chinese country is also considered when examining these qualities (where the likelihood of being electricity impoverished is higher). p_{it} is modeled as

$$p_{it} = Prob\left(\gamma_{it} = 1 \middle| \boldsymbol{x}_{it}\right) = F\left(\boldsymbol{x}_{it}^{\prime}\boldsymbol{\gamma}\right) \tag{1}$$

For each period t, we compute pit, the chance that household I will be energy poor, given the vector of possibly moment explanatory variables.

$$Q_t\left(Y_{\mathrm{or}} \mid I_{\mathrm{t}}\right) = Q_t\left(Y_{\mathrm{it}} \mid I_{\mathrm{ii}}^{Y}\right) \tag{2}$$

The regressions may be used to describe this probability as a function of x_{it}. Assumption: The logistic regression model was used. Therefore, the empirical hypotheses are tested by drawing null and alternative ideas in Eqs. (3) and (4), respectively, which are

$$H_0 : P\left\{F_{Y_{\omega}|P_u}\left\{Q_t\left(I_i^Y\right) \mid I_{it}\right\} = \tau\right\} = 1 \tag{4}$$

$$H_1 : P\left\{F_{Y_e|P_u}\left\{Q_t\left(I_i^Y\right) \mid I_{it}\right\} = \tau\right\}. < 1 \tag{5}$$

By this, energy poverty is estimated. To measure the energy demand dynamics, a logistic cumulative distribution function for the latent variable's error process is taken, and this variable is calculated by Eq. (6) and onwards. Using estimated parameters in conjunction with a pooled bridge technique, an economical model with minimal independent variables is estimated to avoid exact thing issues. Group-resistant error terms are utilized because the error terms for each household are expected to be connected over time.

$$Q_{\mathrm{r}}\left(Y_{\mathrm{i}} \mid I_{\mathrm{t}}\right) = a_i + \sum\nolimits_{k-1}^{q} \gamma^{(k)}(\tau)Y_{i,t-k} + \sum\nolimits_{k-1}^{q} \beta^{(k)}(\tau)X_{ir-k} + \varepsilon_{i,t}(\tau) \tag{6}$$

Every home is regarded as a distinct group. When a given "explain" order evolves, the risk that a family would be energy poor increases by an average percent. Specifically, we are interested in which factors are favorably correlated with one EP measurement but adversely linked with the other, and which variables have a positive or negative association with one EP metric. Still, no significant relationship with other EP measurements, that is,

$$Q_\tau\left(\hat{Y}_{i,t} \mid I_{\Delta u}\right) = \hat{F}_{Y_i}\Big|_{I_z}\left(\tau \mid I_{it}\right) \tag{7}$$

$$\hat{I} \equiv \tfrac{1}{N^2T(T-1)h^{2+}} \sum\nolimits_{i=1}^{N} \sum\nolimits_{j=1}^{N} \sum\nolimits_{t-1}^{T} \sum\nolimits_{x+f}^{T} K_{ijt}\left[1\left\{Y_i \le \hat{Q}_t\left(Y_i \mid I_i\right)\right\} - \tau\right] \cdot\left[1\left\{Y_{is} \le \hat{Q}_t\left(Y_j \mid I_j\right)\right\} - \tau\right] \tag{8}$$

When a country's optimization issue is unrestrained, the energy consumption reaction to dynamic pricing cannot be less than when the problem is limited. This is shown in this chapter. Assuming the limiting factor is a technology that controls how energy-intensive an item is to make, the conclusion is that price increases that lead to improved fuel efficiency cannot be followed by increased energy use. This means that the rebounding impact of a price increase-induced technical development will be weak. Imagine a

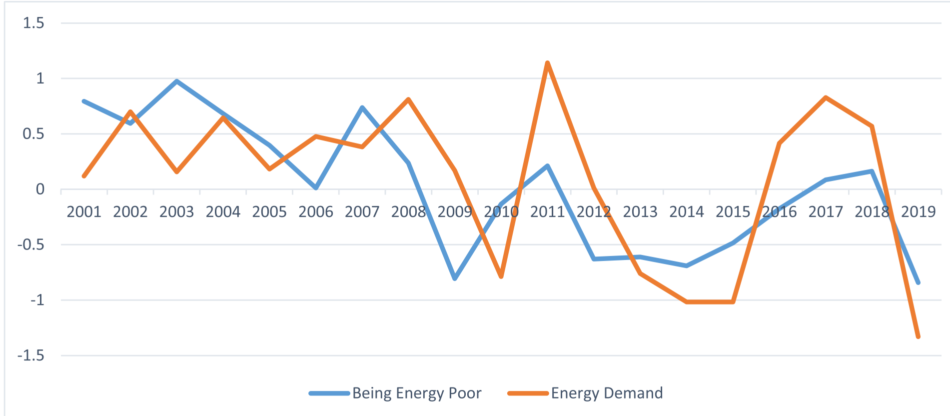

Fig. 1 Energy demand dynamics connection with energy poverty in China

modeling approach of the company's production function to quantify this claim. *Y* is equal to *F*. Energy use is represented by *E*, and other inputs (such as capital, labor, materials, and services) by $z1$, $z2\ldots$, while technological characteristics impact the efficiency of information (such as energy use).

To simplify, we will suppose that the choice of inputs and technology is unrestricted in the long run. In contrast, selecting information and technologies is restricted in the near term. Constricting the short-term selection of a subset of inputs does not affect the overall outcome. We use a symbol to represent the price of power.

Results and discussion

Differences in the incidence of energy poverty—empirical findings

The steep rise in energy costs since 2005 has been linked to an increase in the sample median EP at five times the median income. The 10% indicator represents this rise in the percentage of consumer spending allocated to energy. Price and power start-sharing rises are partially soaked up in LIHC due to its relative essence; the continual steady decline in this way of measuring is also impacted by an excessive specimen of families in devolved governments, where median income grew nearly twice as fast as in China.

A comparison of our estimations with official and more recent data is shown in Fig. 2 for England alone, including the statutory 10% and LIHC numbers. Our indications indicate comparable trends compared to government statistics, yet they are continuously lower. Using gross income instead of net income while compiling results is the most probable reason for the discrepancy. There is a growing discrepancy between our 10% indication and official figures throughout the period. This widening of the gap can be attributed to the rising fuel prices. The official 10% indicator uses modeled EP, which fixes power usage at an "ideal" level.

In contrast, our 10% marker utilizes disclosed EP, which reflects any decrease in energy usage by families in response to higher costs. While actual stats would show a bigger disparity between the EDD and outlay measures, this only highlights the difficulties in using any one official metric in its own right. The knowing society data's "cannot keep the house warm enough in winter" question comes closest to EDD, but only in a few waves, as indicated. Its one-step methodology and more broad character, which omits particular references to cost, explain why it is higher than EDD but well below other formal metrics. The EDD signal has no standard counterparts.

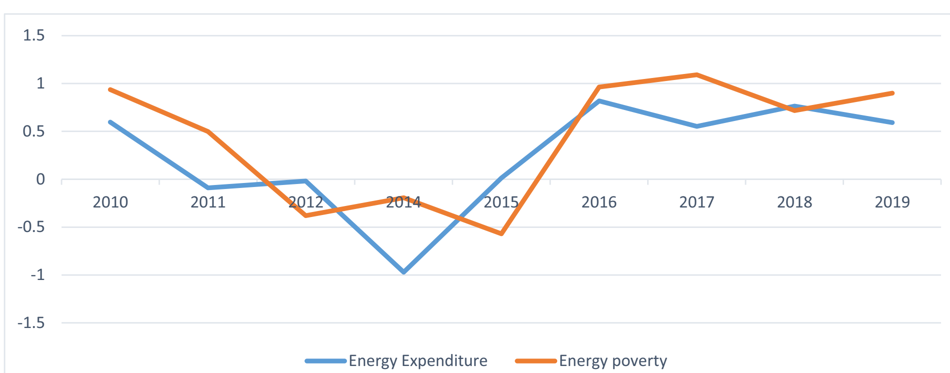

Fig. 2 Energy expenditures role in energy poverty over the sample period

Overlap in energy demand dynamics and energy poverty status

EDD was reported by 10% of LIHC EP families at no time over the study's duration. Using any official EP criteria, this stark disparity shows that at least 95% of families think they can afford warm housing (though we note that the structure of the questions limits their numbers to some extent). In other words, 60% (70%) of people who say they cannot afford appropriate heating are not considered EP by the LIHC (10%) criteria. There is still a more than two-fold increase in the likelihood that a family is energy impoverished, as measured by one of the expenditure-based measures. Families experiencing EDD are also more likely to be fuel poor, mainly if the LIHC indication is considered (see Figs. 1 and 2). The Pearson correlation analysis makes it easy to see these minuscule overlaps amongst EP indicators. All are considerably different from 0 at the 1% level. However, their values vary from 0.511 (between the 10% and LIHC indicators) to less than 0.06 between EDD and each outlay metric (see Table 3). Table 1 shows a correlation between the two new standards to the tiny (but statistical significance) average marginal impact of each EP spending indicator on the likelihood of reporting in Tables 1 and 2.

For the binary 10% and LIHC indicators, Table 1 demonstrates how revenue and EP relate to the EDD. For example, the quasi correlations between EP, EP (the proportion of average earnings dedicated to EP), and income. This means that all three of these variables are represented as basis functions. If EP is the only independent factor (Table 3), there is no highly significant association between EP and EDD (at the 10% level). However, EP has a statistically significant positive relationship with EDD (Table 4), while the connection between family income and EDD is weakly positive (Tables 4 and 5).

When both EP and income are included in the model as distinct quadratic variables instead of as EP, the relationships with EDD are shown in Tables 6 and 7. Suppose income and EP are used as actual values in Table 6. In that

Table 2 Potential variation in the study constructs' nexus (annual response)

Years	Controls	Being energy poor	Energy demand
2001	0.296	0.794	−0.676
2002	0.252	0.595	0.105
2003	0.227	0.975	−0.819
2004	0.346	0.683	−0.039
2005	0.298	0.396	−0.213
2006	0.475	0.011	0.466
2007	0.787	0.737	−0.355
2008	0.645	0.237	0.574
2009	0.833	−0.806	0.975
2010	0.247	−0.134	−0.653
2011	0.836	0.212	0.929
2012	0.314	−0.631	0.643
2013	0.966	−0.612	−0.149
2014	0.102	−0.691	−0.327
2015	0.279	−0.485	−0.533
2016	0.555	−0.176	0.591
2017	0.202	0.086	0.742
2018	0.938	0.163	0.407
2019	0.494	−0.842	−0.488

Table 1 Descriptive estimates

	(a)	(b)	(c)	(d)
	Energy demand dynamics		Energy poverty dimensions	
Indicators	High demand	Demand failure	Currently poor	Estimated score
Panel (1) Casual variable: energy demand dynamics				
EP score	0.103*	0.954	0.217*	0.541*
	(0.041)	(0.298)	(0.321)	(0.837)
	(0.863)	(0.558)	90.933)	(0.763)
C	0.823*	0.635*	0.119*	−0.399*
	(0.838)	(0.613)	(0.299)	(0.362)
Controls	0.274	0.2171	0.561	0.687
Panel (2) Casual variable: energy supply dynamics				
EP score	0.971*	0.316	0.931*	0.874
	(0.508)	(0.825)	(0.277)	(0.576)
	(0.852)	(0.127)	(0.438)	(0.786)
C	0.521*	0.672	0.084*	0.595
	(0.384)	(0.617)	(0.111)	(0.455)
Controls	0.133	0.745	0.705	0.843

*Significance level 5%

Table 3 Energy poverty in China (household demographics)

Demographics	Score (2001–2009)	Score (2010–2019)
Male	0.712	0.525
Female	0.382	0.484
At urban level	0.161	0.145
At rural level	0.322	0.491
Age = 25 years	0.842	−0.111
Age < 25 years	0.886	0.471
Age > 25 years	0.685	0.945

Table 4 Energy expenditure share in household and energy poverty in China (last 10 years)

Years	Energy expenditure	Energy poverty
2010	0.597	0.338
2011	−0.089	0.588
2012	−0.018	−0.361
2014	−0.971	0.779
2015	0.013	−0.581
2016	0.818	0.146
2017	0.552	0.538
2018	0.764	−0.047
2019	0.591	0.309

case, Wald tests reject the hypothesis that their scores are inverses, showing that they should be treated as distinct variables rather than merged as EP in the final model. Even after controlling for household income in Tables 6 and 7, there is a statistically meaningful link between EDD and EP. In contrast, the size of the link stays minor. Increasing family income by $1000 has a 0.1% reduction in the likelihood of EDD, whereas increasing EP by $100 has a 0.05% rise in the possibility of EDD (Table 6). The linear element's coefficient for EP is statically essential, demonstrating that the mean marginal effect is modest rather than an average negative and positive impact.

Net annual dwelling expenses (the third component of the LIHC indicator) and the first EDD lag are shown in Table S3 as explanatory variables. The relationship between net housing costs and EDD is positive and nonlinear even after accounting for EP, income, and the EDD's initial lag. As in the previous year, being EDD power poverty increases the chances of being so in the current year by 23% when EP, income, and net housing expenses are considered (Table 3). Because it might obscure correlations with other factors that change little over time, this lagged variable is not included in the bivariate analysis below. There is a stronger correlation between feeling unable to buy energy and having 10% EP, according to Waddams Price (2018). This may be due to the study's low-income sample and perception-based pricing measures. It is difficult for families to identify as energy-poor using information gleaned from the low rates of perception-based EP.

For example, households' perceptions of where energy becomes costly versus the limits used in calculating EP metrics based on spending alone may explain the gap between perceived energy affordability vs. expenditure affordability. In other words, the limit may be elsewhere, or homeowners could see energy affordability as a range rather than an absolute "yes/no," as presented in the BHPS question. Homeowners' (rather than critics') perceptions of an expensive EP spending level were not explicitly addressed in the expenditure-based definitions. Households may also view energy as a necessity, in which case they will spend a large portion of their income on it to maintain adequate warmth. As previously mentioned, the profitability question would not have been asked if a household did not report insufficient levels of heat. High EP may have the primary effect of limiting one's ability to purchase other items.

Table 5 Energy demand nexus with energy poverty indication

	DV: energy poverty					
	OLS		Fisher effect		Fishes effect on 2SLS	
Panel (1)	(a1)		(a2)		(a3)	
First-stage results	0.616*	−0.978	0.361*	−0.034	0.268*	−0.293
Hansen J statistic p-value	0.022		0.025		0.009	
Kleibergen–Paap rk Wald F-statistic	−0.163		0.252		0.599	
Average county energy poverty	0.245		−0.316		0.101	
Panel (2)	(b1)		(b2)		(b3)	
First-stage results	0.133*	0.289	0.603*	−0.228	0.516*	−0.326
Hansen J statistic p-value	0.000		0.000		0.000	
Kleibergen–Paap rk Wald F-statistic	0.062		0.882		0.752	
Average county energy poverty	0.339		0.357		0.814	

*Significance level 5%

Table 6 Sensitivity analysis

Years	ED score	EP score
2001	0.083	0.324
2002	−0.467	−0.874
2003	0.607	0.037
2004	0.011	−0.398
2005	0.129	−0.197
2006	−0.783	0.317
2007	−0.362	−0.295
2008	0.295	−0.359
2009	−0.714	0.278
2010	0.184	−0.948
2011	−0.961	−0.396
2012	−0.888	0.416
2013	0.288	−0.072
2014	0.704	0.302
2015	−0.681	0.443
2016	−0.427	−0.086
2017	0.626	0.736
2018	0.087	−0.397
2019	−0.059	0.151

In contrast, a family that reports EDD but spends a small percentage of its income on EP may limit its energy use because it is unaffordable. Instead of utilizing what may be predicted as desired, this is the downside of using reported actual expenditures: energy rationing is not seen. Both data on the temperature homeowners want, and data on the temperatures achieved in the home are required to determine whether or not there is an issue and how to effectively handle it. We suggest gathering fresh information on individual home temperature preferences and realizations is critical in determining the nature of any problem and the best way to solve it.

Regarding other traits, the most significant variation is often seen in the age of the household's head. Homes with a leader 65 years or older make up a larger share of the sample's resource-poor families, while homes classified as EDD had a smaller percentage of older household heads. This disparity is much more pronounced in homes where the head is over 75. There is a higher percentage of homes in Northern Ireland with no gasoline hookup than the way of representing in all three EP categories.

We continue our descriptive analysis above should investigate the associations between significant exogenous households and each of EP's three EP indicator values. Different EP metrics have different relationships with other household characteristics, especially regarding how they relate to household head age, although there are certain discrepancies regardless of which EP is used.

Robustness

Various experiments have verified the robustness of the findings in Table 4. All factors' variance inflation factor (VIF) was calculated to see whether they were likely to be levels of diversity. A maximum value of 2.14 was found in our VIFs, showing that co-integration was not a significant issue in our model. Using OLS and 2SLS link functions, the regressions in Table 4 have also been conducted a second time. Using various link algorithms yields essentially the exact log-likelihoods every time. This is the norm. In every case except one, calculating the likelihood function with the most significant (least damaging) log-likelihood is best. Given this little difference, employing the empirical link function has no effect on Table 1 of Table 4's amplitude or relevance for the EDD indicator; as a result of this slight increase in log probability, using the empirical computational link function has no impact.

We have uncovered the connections among EP measures and other explaining factors by pooling past research, which uses all of the available data. Due to the substantially lower sample size, the patterns of connections between the three EP measures may alter if just one year's worth of data were available for investigation. According to Tables 4 and 2, we have found an association among household heads aged 65 to 75 and 10% EP (significant at the 5% level), while comparable correlation coefficients conducted individually for each year reveal an equally statically strong positive relation only in the 2008–2009 wave (Tables 4 and 2; see Fig. 1).

Discussion

We ran the experiment in three different ways. In the first case, companies cannot change their technological infrastructure (Aristondo and Onaindia 2018). For this case, we set the variable to a relatively large amount, implying that the business would lose money if it changed its which was before technological selection (Maxim et al. 2016). Corporations can choose the technologies they want to use (Papada and Kaliampakos 2018). According to our hypothetical woman's design in "Data and methodology", companies cannot alter technologies for all their invested capital simultaneously in this situation (Scarpellini et al. 2019). A company may only adapt its expertise once for worth bought in this time and for a tiny percentage (10%) of its prior investment. Third, we enable 90% of the firm's capital stock to quickly alter its innovation (Nussbaumer et al. 2013). The values of critical parameters utilized in the simulation are summarized in Table 1. For now, we will compare the first two scenarios and refer to the third scenario when needed to better understand how slow technological adaptation affects the effect of process parameters (Aristondo and Onaindia 2018; Walker 2014).

Empirical studies also support this (Halicioglu 2007). In 14 of the 19 industries studied, Butler et al. (2014) find that the null hypothesis of zero substitution is not disproved. Kuper and van Soest (2003) and Liu (2004) both came to similar conclusions (2004). According to the model, demand will be elastic in the long term at a constant (Hong et al. 2016). It is greater than Liu's (2004) estimation of 0.2 for electricity (Shove et al. 2015). Notably, the flexibility of replacement values greater than 0.45 resulted in unpredictability (Iacopini et al. 2020). Because of the vast range of long-term empirical estimates in the literature, it is impossible to predict how much energy consumption will respond to changes in carbon source costs in the long run (Lescaroux 2011). It also suggests that our mathematical figure's predictions about the magnitude of the impacts are speculative (Ruellan et al. 2016). It is also possible that the quantitative outcomes will be substantially different in other nations, particularly those whose economies are less reliant on coal (Hui and Walker 2018). Our numerical forecasts primarily demonstrate the possible economic implications of long-term energy-saving modifications (Kroll et al. 2012).

The coal tax rate for energy generation is the same in all scenarios, and in the first year, it generates around 2.8% of total energy efficiency (Shove and Walker 2014). Figure 2 shows how much electricity will be used in each scenario. When companies are not permitted to change their equipment, it results in weak little (Hekkenberg et al. 2009). Energy-intensive industries' declining share and a decline in aggregate output are the primary reasons behind this (both caused by an increase in energy price). It is possible that technologies may be improved, resulting in a more significant long-term decline because companies would transition to more energy-efficient manufacturing processes. When companies can make instantaneous changes to their whole invested capital, the reduction in energy usage occurs quickly once the carbon price is implemented (Sisodia et al. 2016). Even though organizations may make modest technological changes, the initial impact is comparable to no alteration. China's power money supply grows over time, and energy use settles into a new long-term stable state. The long-term outcomes are the same regardless of whether tech is adjusted gradually or immediately. Simulating three alternative values of the variable yielded the same results. Higher values correlate to lower estimated long-run elasticity of capital-to-energy substitution and, as predicted, have a lesser long-term impact on energy than lower values. The energy consumption pattern converging to a new long-term steady state is the same for everyone.

In the raw materials industry, the direction energy usage takes directly affects CO2 emissions and jobs. The primary source of CO_2 emissions in Poland is energy production; hence, reducing energy consumption decreases CO_2 emissions (Fig. 1). However, in the long term, the decline is more significant in circumstances with progressive technological adjustment than in settings where modification is not conceivable. The mining and quarrying industry's job trends follow a similar pattern (Fig. 2). Coal mining dominates this industry in China, providing an intermediary input to the country's coal-based energy sector. As a result, as energy demand declines, coal jobs will also go away.

Conclusion and policy implications

To create a uniform basis for academic research, it is essential to understand the distinctions between the metrics and what they are measuring. This will allow researchers to evaluate the incidence of EP through time and between locations. The increasing research in many socioeconomic kinds and the publications referenced in "Literature review" above have proven that such comparison may illuminate the character of house heating concerns in various climates, regions, and economic development situations. Associating each EP measure with a particular attribute of a home helps to identify people who are at risk while also pointing to possible avenues for implementing policy. Our research reveals the methodological issues that underlie EP estimates and how several measures illuminate the nuanced nature of the underlying problem of insufficient home thermoregulation. However, even though the data is from a particular regime and cannot be used to make a modern comparison, their study confirms and demonstrates these broader principles.

Because of its persistence among low-income families, EP has been a prominent policy concern. On the other hand, the introduction of low-carbon energy strategies would result in additional expenses, such as the stranded assets of boilers and systems built for dioxide energies and the altered distribution networks. These extra expenses will alter the price-to-energy-use ratio for individual families, bringing new problems for energy accessibility. Many previous efforts have targeted increasing the home energy economy, and specific legislation may try to address both EP and environmental problems.

There has been a lot of debate over which one is the greatest. EP might be measured using a composite metric. It is apparent from this study's research that regularly used and recommended EP measurements do not overlap. Many households are labeled as being energy poor according to just one sign, and only a tiny number by all three. This is because the total prevalence of EP varies substantially by each of the three indicators. It is a classic case of "what assessment is generally controlled," since programs and their outcomes will vary depending on the indicator used. It also reveals basic variations in what each indicator measures and challenges policymakers to reevaluate their approach to EP relief.

This example illustrates how the selection of an indication directly impacts the arguments in favor of particular families. It is important to note that each EP gauge has limits. One example is the employment of engineering models to estimate the costs of obtaining which was before surface temperatures rather than measuring the temperatures obtained in homes, much alone linking them to the desires of individual families. With the possibility of losing much of the complexity and nuance of domestic knowledge that affects each measure, choosing one of the EP indicators discussed here or creating some new methodology is risky. Rather than throw out the data gathered from each test, we suggest adding substantial evidence, such as direct measurements of in-home temperature changes and proof of what temperature changes a customer's energy demand. Few massive studies have recently attempted to measure the temperatures accomplished in various households, despite Hills' (2012) advice. With the introduction of an intelligent thermostat, massive temperature records have become increasingly possible, giving policymakers a better chance to address EP directly. For example, the British Gas Hive system is installed in over 1.5 million homes in the UK. A greater understanding of the phenomena and the advantages that each home derives from energy consumption would be possible with temperature data, as would policy targeting and policy evaluation. The present EP indicators run the danger of erroneous exclusionary and a skewed understanding and policy on the frequency.

Author contribution Write up corrections, data curation, and supervision: Jianhe Wang; visualization, editing, and writing of draft: Ziman Xiang; writing and software: Xiaohan Jiang; writing, editing, and visualization: Lei Wang; conceptualization, methodology, review, and visualization: Lei Chang.

Data availability Data is publicly available at mentioned sources in data section.

Materials availability Data is publicly available at mentioned sources in data section.

Declarations

Ethical approval and consent to participate We declare that we have no human participants, human data, or human issues.

Consent for publication We do not have any individual person's data in any form, and we give consent for publication in true letter and spirit.

Competing interests The authors declare no competing interests.

References

Adusah-Poku F, Takeuchi K (2019) Energy poverty in Ghana: any progress so far? Renew Sustain Energy Rev 112:853–864

Agyekum EB, Amjad F, Mohsin M, Ansah MNS (2021) A bird's eye view of Ghana's renewable energy sector environment: a multi-criteria decision-making approach. Util Policy 70:101219

Ahmad S, Islam T, Sadiq M, Kaleem A (2021) Promoting green behavior through ethical leadership: a model of green human resource management and environmental knowledge. Leadersh Org Dev J 42(4):531–547

Alemzero DA, Iqbal N, Iqbal S, Mohsin M, Chukwuma NJ, Shah BA (2021) Assessing the perceived impact of exploration and production of hydrocarbons on households perspective of environmental regulation in Ghana. Environ Sci Pollut Res 28(5):5359–5371

Anh Tu C, Chien F, Hussein MA, Yanto Ramli MM, Psi MM, Mochamad SS, Iqbal S, Bilal AR (2021) Estimating role of green financing on energy security, economic and environmental integration of BRI member countries. Singapore Econ Rev. https://doi.org/10.1142/S0217590821500193

Anser MK, Yousaf Z, Nassani AA, Abro MMQ, Zaman K, Kabbani A (2020) Evaluating ecological footprints through inbound tourism, population density, and global trade. Pol J Environ Stud. https://doi.org/10.15244/pjoes/122445

Aristondo O, Onaindia E (2018) Counting energy poverty in Spain between 2004 and 2015. Energy Policy 113:420–429

Baloch ZA, Tan Q, Iqbal N, Mohsin M, Abbas Q, Iqbal W, Chaudhry IS (2020) Trilemma assessment of energy intensity, efficiency, and environmental index: evidence from BRICS countries. Environ Sci Pollut Res 27(27):34337–34347

Barnes DF, Khandker SR, Samad HA (2011) Energy poverty in rural Bangladesh. Energy Policy 39(2):894–904

Bednar DJ, Reames TG (2020) Recognition of and response to energy poverty in the United States. Nat Energy 5(6):432–439

Bhide A, Monroy CR (2011) Energy poverty: a special focus on energy poverty in India and renewable energy technologies. Renew Sustain Energy Rev 15(2):1057–1066

Bouzarovski S, Petrova S, Sarlamanov R (2012) Energy poverty policies in the EU: a critical perspective. Energy Policy 49:76–82

Bradshaw J, Hutton S (1983) Social policy options and fuel poverty. J Econ Psychol 3(3-4):249–266

Butler C, Parkhill KA, Shirani F, Henwood K, Pidgeon N (2014) Examining the dynamics of energy demand through a biographical lens. Nat Cult 9(2):164–182

Chien F, Pantamee AA, Hussain MS, Chupradit S, Nawaz MA, Mohsin M (2021) Nexus between financial innovation and bankruptcy: evidence from information, communication and technology (ict) sector. Singap Econ Rev :1–22. https://doi.org/10.1142/S0217590821500181

Culver L (2017) Energy poverty: what you measure matters. In Proceedings of the Reducing Energy Poverty with Natural Gas: Changing Political, Business and Technology Paradigms Symposium, Stanford, CA, USA, pp. 9–10

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

Deller D, Waddams C (2018) UK energy expenditure shares–a long term view

Halff A, Sovacool BK, Rozhon J (eds) (2014) Energy poverty: global challenges and local solutions. Oxford University Press, Oxford

Halicioglu F (2007) Residential electricity demand dynamics in Turkey. Energy Econ 29(2):199–210

Hekkenberg M, Moll HC, Uiterkamp AS (2009) Dynamic temperature dependence patterns in future energy demand models in the context of climate change. Energy 34(11):1797–1806

Herrero ST (2017) Energy poverty indicators: a critical review of methods. Indoor Built Environ 26(7):1018–1031

Hong L, Zhou N, Feng W, Khanna N, Fridley D, Zhao Y, Sandholt K (2016) Building stock dynamics and its impacts on materials and energy demand in China. Energy Policy 94:47–55

Hui A, Walker G (2018) Concepts and methodologies for a new relational geography of energy demand: social practices, doing-places and settings. Energy Res Soc Sci 36:21–29

Iacopini I, Schäfer B, Arcaute E, Beck C, Latora V (2020) Multilayer modeling of adoption dynamics in energy demand management. Chaos: An Interdisciplinary Journal of Nonlinear Science 30(1):013153

Iqbal S, Bilal AR (2021) Energy financing in COVID-19: how public supports can benefit?. China Finance Rev Int 12(2):219–240
Iqbal W, Tang YM, Chau KY, Irfan M, Mohsin M (2021b) Nexus between air pollution and NCOV-2019 in China: application of negative binomial regression analysis. Process Saf Environ Prot 150:557–565
Iqbal S, Taghizadeh-Hesary F, Mohsin M, Iqbal W (2021a) Assessing the role of the green finance index in environmental pollution reduction. Stud Appl Econ 39(3). https://doi.org/10.25115/eea.v39i3.4140
Iram R, Anser MK, Awan RU, Ali A, Abbas Q, Chaudhry IS (2021) Prioritization of renewable solar energy to prevent energy insecurity: an integrated role. Singapore Econ Rev 66(02):391–412
Kaygusuz K (2011) Energy services and energy poverty for sustainable rural development. Renew Sustain Energy Rev 15(2):936–947
Kroll F, Müller F, Haase D, Fohrer N (2012) Rural–urban gradient analysis of ecosystem services supply and demand dynamics. Land Use Policy 29(3):521–535
Kuper GH, van Soest D (2003) Does oil price uncertainty affect economic activity?. https://doi.org/10.2139/ssrn.379160
Lescaroux F (2011) Dynamics of final sectoral energy demand and aggregate energy intensity. Energy Policy 39(1):66–82
Li W, Chien F, Hsu CC, Zhang Y, Nawaz MA, Iqbal S, Mohsin M (2021a) Nexus between energy poverty and energy efficiency: estimating the long-run dynamics. Resour Policy 72:102063
Li W, Chien F, Ngo QT, Nguyen TD, Iqbal S, Bilal AR (2021b) Vertical financial disparity, energy prices and emission reduction: empirical insights from Pakistan. J Environ Manag 294:112946
Li Y, Wang S, Xu T, Li J, Zhang Y, Xu T, Yang J (2021c) Novel designs for the reliability and safety of supercritical water oxidation process for sludge treatment. Process Saf Environ Prot 149:385–398
Liu J (2004) Macroeconomic determinants of corporate failures: evidence from the UK. Appl Econ 36(9):939–945
Maxim A, Mihai C, Apostoaie CM, Popescu C, Istrate C, Bostan I (2016) Implications and measurement of energy poverty across the European Union. Sustainability 8(5):483
Meyer S, Laurence H, Bart D, Middlemiss L, Maréchal K (2018) Capturing the multifaceted nature of energy poverty: lessons from Belgium. Energy Res Soc Sci 40:273–283
Mohsin M, Hanif I, Taghizadeh-Hesary F, Abbas Q, Iqbal W (2021a) Nexus between energy efficiency and electricity reforms: a DEA-Based way forward for clean power development. Energy Policy 149:112052
Mohsin M, Kamran HW, Nawaz MA, Hussain MS, Dahri AS (2021b) Assessing the impact of transition from nonrenewable to renewable energy consumption on economic growth-environmental nexus from developing Asian economies. J Environ Manag 284:111999
Nussbaumer P, Bazilian M, Modi V (2012) Measuring energy poverty: focusing on what matters. Renew Sustain Energy Rev 16(1):231–243
Nussbaumer P, Nerini FF, Onyeji I, Howells M (2013) Global insights based on the multidimensional energy poverty index (MEPI). Sustainability 5(5):2060–2076
Okushima S (2016) Measuring energy poverty in Japan, 2004–2013. Energy Policy 98:557–564
Pachauri S, Mueller A, Kemmler A, Spreng D (2004) On measuring energy poverty in Indian households. World Dev 32(12):2083–2104
Papada L, Kaliampakos D (2016) Measuring energy poverty in Greece. Energy Policy 94:157–165
Papada L, Kaliampakos D (2018) A stochastic model for energy poverty analysis. Energy Policy 116:153–164
Ruellan M, Park H, Bennacer R (2016) Residential building energy demand and thermal comfort: Thermal dynamics of electrical appliances and their impact. Energy and Build 130:46–54
Sagar AD (2005) Alleviating energy poverty for the world's poor. Energy Policy 33(11):1367–1372
Sareen S, Thomson H, Herrero ST, Gouveia JP, Lippert I, Lis A (2020) European energy poverty metrics: Scales, prospects and limits. Glob Transit 2:26–36
Scarpellini S, Hernández MAS, Moneva JM, Portillo-Tarragona P, Rodríguez MEL (2019) Measurement of spatial socioeconomic impact of energy poverty. Energy Policy 124:320–331
Shove E, Walker G (2014) What is energy for? Social practice and energy demand. Theory Cult Soc 31(5):41–58
Shove E, Watson M, Spurling N (2015) Conceptualizing connections: energy demand, infrastructures and social practices. Eur J Soc Theory 18(3):274–287
Sisodia GS, Sahay M, Singh P (2016) System dynamics methodology for the energy demand fulfillment in India: A preliminary study. Energy Procedia 95:429–434
Sun L, Qin L, Taghizadeh-Hesary F, Zhang J, Mohsin M, Chaudhry IS (2020) Analyzing carbon emission transfer network structure among provinces in China: new evidence from social network analysis. Environ Sci Pollut Res 27(18):23281–23300
Tehreem HS, Anser MK, Nassani AA, Abro MMQ, Zaman K (2020) Impact of average temperature, energy demand, sectoral value added, and population growth on water resource quality and mortality rate: it is time to stop waiting around. Environ Sci Pollut Res 27(30):37626–37644
Thomson H, Bouzarovski S, Snell C (2017a) Rethinking the measurement of energy poverty in Europe: a critical analysis of indicators and data. Indoor Built Environ 26(7):879–901
Thomson H, Snell C, Bouzarovski S (2017b) Health, well-being and energy poverty in Europe: a comparative study of 32 European countries. Int J Environ Res Public Health 14(6):584
Tiep NC, Wang M, Mohsin M, Kamran HW, Yazdi FA (2021) An assessment of power sector reforms and utility performance to strengthen consumer self-confidence towards private investment. Econ Anal Policy 69:676–689
Waddams Price C (2018) Back to the future? Regulating residential energy markets. Int J Econ Bus 25(1):147–155
Walker G (2014) The dynamics of energy demand: change, rhythm and synchronicity. Energy Res Soc Sci 1:49–55
Xian J, Li B, Huang H (2020) Transformational leadership and employees' thriving at work: the mediating roles of challenge-hindrance stressors. Front Psychol 11:1400
Xu Y, Chen Z, Peng MYP, Anser MK (2020) Enhancing consumer online purchase intention through gamification in China: perspective of cognitive evaluation theory. Front Psychol 11:581200. https://doi.org/10.3389/fpsyg.2020.581200
Yousaf S, Anser MK, Tariq M, Jawad SURS, Naushad S, Yousaf Z (2020) Does technology orientation predict firm performance through firm innovativeness?. World J Entrepr Manag Sustain Dev
Yuan H, Wang Z, Shi Y, Hao J (2021) A dissipative structure theory-based investigation of a construction and demolition waste minimization system in China. J Environ Plan Manag :1–27. https://doi.org/10.1080/09640568.2021.1889484
Zhang D, Mohsin M, Rasheed AK, Chang Y, Taghizadeh-Hesary F (2021) Public spending and green economic growth in BRI region: mediating role of green finance. Energy Policy 153:112256

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.