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Inequality and energy: Revisiting the relationship between disparity of income distribution and energy use from a complex systems perspective

Fouad Khan[a,b,*], Paul Heinecker[c]

[a] Central European University, Nador utca 9, Budapest 1056, Hungary
[b] WWF Luc Hoffmann Institute, Avenue du Mont-Blanc 27, 1196 Gland, Switzerland
[c] University of Applied Science, Weesperzijde 190, Amstelcampus, 1097 DZ Amsterdam, Netherlands

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ABSTRACT

To consider the impacts of economic inequality on energy consumption efficiency we need indicators that take into account the complexity of the economic and energy systems. We also need decision support tools that help incorporate such indicators into policy analysis. Drawing inspiration from urban studies and ecology, in this paper we develop a scaling indicator for income disparity in national economies that is a measure of system complexity and does not presuppose any distribution as ideal. The scaling indicator is calculated for 2010 income distribution data for countries. We show that rising disparity – measured using this indicator calculated; a) for distributions of incomes across consecutive twentieth percentiles of population in national economies and; b), for distributions of population density in census blocks in metropolitan statistical areas affects energy consumption efficiency in a diametrically different manner in cities and nation states leading to a higher urban carbon footprint while increasing energy efficiency nationally. The different nature of these two systems explains the results. We then modify tools for visualizing complexity from urban studies and ecology to explore the correlation between income disparity and energy efficiency in national economies.

The adverse impacts of inequality in economic systems especially on human well-being have been extensively documented in literature going back more than three decades [1]. Recent social, neurological [2] and even evolutionary [3] evidence points toward the necessity for addressing the rising inequality in economic systems. Literature that presents evidence for rising inequality in economic systems especially in developed nations post World War II [4,5], has reinvigorated the debate on income inequality [6–9]. However, such studies are often criticized for use of 'mean' or 'average' measures that do not capture non-linearity in systems [10]. One way to study disparity or inequality in complex systems is to look at scaling within systems. Living organisms and many other dynamical systems have been shown to obey a power law in scaling of the sizes of their various elements [11–13]. The impact of scaling on sociopolitical conflict has been explored in detail in literature [14]. In US the relationship between income distribution and energy and environmental indicators has also been studied [15]. In growing economies such as China and India too income inequality has been shown to affect energy consumption and CO_2 emissions [16] though in the long run in some instances the effect was not found to be statistically significant [17]. Part of the problem with exploring the correlation between inequality or disparity in systems and its effects on energy consumption is the dearth of indicator systems that can take into account the complexities that underlie such an interaction [18]. Indicator systems in economics, environment or energy consumption by and large continue to be 'linear' in that they measure change in particular characteristics or parameters as not critically affecting all other elements of the system in a systemic way and being affected by the system, but respond to a limited, often no more than one or two stimuli. While complex integrated assessment models do take into account the density of networked interactions that underlie an economic system to a certain extent, the measurements or indicators themselves, almost by their very nature do not consider 'non-linearity' in dynamics of the system [19]. This fact in itself makes it difficult to study the correlation between 'inequality' and other system wide indicators because the impacts of inequality or 'disparity' in the system largely often emerge in the form of non-linear responses. Between certain values any change in inequality may not have an effect on system wide parameters but then minor changes may result in sudden large perturbations [20,21]. While mechanisms have been proposed in literature that show why response to income inequality is nonlinear, there is a dearth of indicators and quantitative assessments on the subject that bring empirical evidence to bear on the theoretical understanding of economy wide non-linearity

* Corresponding author at: Central European University, Nador utca 9, Budapest 1056, Hungary.
E-mail addresses: fouadmkhan@gmail.com, fouad.khan@us.nature.com (F. Khan).

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[18]. the social dynamics of energy systems still need further investigation from multiple perspectives [22] especially with incorporation of the complexity of the systems into analysis. This work takes some steps towards addressing these shortcomings.

Recently it has been demonstrated that system resilience is a function of system heterogeneity among other factors [23]. This heterogeneity has been shown to arise from the hierarchical structure of the system for ecological systems [24] and expresses itself structurally in the form of very specific scaling in distribution of sizes of elements. The classes of sizes of given parameter are distributed at various scales such that the number of elements p, at each scale x are related according to the equation px^m = constant [25] where m is the exponent of the power law with values lying between 0.75 and 2.5, also sometimes called the fractal dimension. In other words, typically these systems do not have aberrantly sized elements and the number of component elements decreases as the scale to which the element belongs increases in size; the bigger an element is, the lesser its population in the system [12,25–28]. In network terms the system exhibits 'scale free' structuring [29]. Such structuring has been discovered in a number of anthropogenic dynamical systems especially cities [25,30–34]. It was recently shown that indicators based on the exponent of the power-law can be developed based on this scaling for cities that help explain energy consumption behavior in the urban system [35]. The exponent of power-law distribution can thus serve as a scaling indicator which provides a much more comprehensive picture of disparity in systems.

In this paper we develop just such an indicator for measuring comparative disparity in national economies. The indicator is formulated and calculated for income distribution across consecutive 20th percentiles. We then show that comparative disparity measured using this scaling indicators affects energy consumption efficiency positively in national economies in a manner dissimilar to the way it affects energy consumption efficiency in cities. We then explore the systemic reasons for this difference in results. Further we modify two tools for visualizing complexity from urban studies and ecology and apply them to the study of correlation between energy efficiency and income inequality in national economies [35].

1. Methods and materials

Economies are complex adaptive systems and should also exhibit similar scaling properties as other complex systems. In order to see how scaling in economic systems affect environmental indicators we looked at a fractal dimension based scaling indicator of distribution of income. The environmental or direct sustainability indicator studied was per capita energy usage. The data was obtained from the World Bank open data platform [36]. Data from the year 2010 was used as that provided us with the biggest set of countries for which income distribution data was available. In this case the primary limitation was income distribution data which was available for only a small number of countries. The data is shown in Appendix A.

Fractal dimension based scaling indicator of national income distribution was calculated by plotting cumulative income share against the cumulative population percentage. Once plotted on log–log scales the resulting slope of the line would be the fractal dimension based scaling indicator of the distribution of income within the country.

To derive our exponent we first start with the formula for the box-counting dimension, as expressed by Eq. (1) [25]. In box-counting method a grid of 'boxes' is layered on a map of the city, that divides the spatial spread of the city into different populated areas, each with a different intensity of urban land use or in other words a different land use coverage.

$$D = \frac{\log N_x}{\log\left(\frac{1}{x}\right)} \tag{1}$$

Where,

D = box counting dimension

x = certain percentage (or range of percentages) of area of the box covered by land use

N_x = Number of boxes falling within range x

Instead of a map we have an extensive data set of the distribution of income by percentage of population. So instead of overlaying a grid of 'boxes' on a map, we will split the population into virtual boxes, each covering 20% of population. So in our methodology the 'box' of the box-counting method is any given 20% population block.

In box counting method for cities the next step is to count all the boxes that fall within a certain range of land use coverage; say 3 out of 40 boxes have between thirty to forty percent of their area covered by urban land use. This is designated by the term N_x in Eq. (1). For our methodology the congruent count will be the percentage of income points that fall within a certain population percentile block. Fig. 1 explains how our method compares to the box counting method.

So if, a_i = *percentage of income held by population block i* and p = *percentage of population in each block*, then cumulative income a for j^{th}, p percentile segment of population will be given by;

$$a_j = \sum_{i=1}^{j} a_i$$

Since for our scaling exponent, the no. of boxes N_x falling within a certain range x, is simply the percentage of income share falling within the percentile j; a_j, N_x can be written simply as;

$$N_x = a_j = \sum_{i=1}^{j} a_i$$

Similarly x for any given percentile j will be given as the total population falling within percentile j. Therefore $x = 1/(j \times p)$. The scaling indicator for our calculation, say D_s can now be expressed as;

$$D_s = \frac{\log N_x}{\log\left(\frac{1}{x}\right)} = \frac{\log a_j}{\log\left(\frac{1}{x}\right)} \tag{2}$$

Using Richardson-Mandelbrot slope [37] now the value of D_s will be calculated by plotting a_j and $1/x$ on log–log scale and estimating the slope of the regression line as shown in Fig. 1. As a_j and x are measured in percentage, D_s is a dimensionless quantity.

The indicator is a measure of disparity within the system. The greater the value of the indicator the lesser the disparity. Compare the two countries in Fig. 2 for instance; United States has higher income share held by a lesser percentage of population compared to Denmark. Thus the starting point for income share for the US (income of 20% richest people) is higher than Denmark and slope of the trend line is lesser. This slope of the trend line thus captures the disparity in the system. The higher the slope or scaling indicator, the lesser the disparity.

The scaling indicator values were calculated by plotting on log–log scale the cumulative income distribution and cumulative population percentage and taking the slope of the regression line. The r-squared value was greater than 0.95 for all the linear fits for all countries, indicating strong power law distribution. The values are shown in the Appendix A. It should be noted here however that of the variables considered in this plotting the clustering of population or binning (into 20th percentiles) was constant and only the wealth distribution varied leaving only one degree of freedom. The high R values are only indicative of a power law distribution and not necessarily predictive accuracy.

A similar indicator (though with opposing directionality) has been developed for cities in literature and has been shown to have a negative correlation with energy efficiency. For cities as the disparity measured using this indicator goes up, the energy efficiency decreases [35].