Apprehending energy efficiency: what is the cognitive value of hypothetical shocks?

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Abstract

This article attempts to explain the macroeconomic drivers of energy efficiency, i.e. the capacity to generate real output from a given energy base. The here-introduced empirical research suggests the existence of a cycle in socio-economic development, where an increasing consumption of energy, whilst counter-efficient on the short run, produces beneficial structural change in national economies and brings, as a result, a delayed improvement in energy efficiency. Surprisingly, the most explanatory power can be derived from the available macroeconomic data when the general theoretical construct of exponential progression is used to simulate a hypothetical deep shock, having occurred in 1989, and sending waves of decreasing strength over the period 1990 – 2014.

Keywords: energy, energy efficiency, energy intensity, technological change

Introduction

Since 2012, the global economy has been going through an unprecedentedly long period of expansion in real output[1]. Whilst the obvious question is "When will it crash?", it is interesting to investigate the correlates of this phenomenon in the sector of energy. In other terms, are we, as a civilisation more energy-efficient as we get (temporarily) much more predictable in terms of economic growth? The very roots of this question are to find in the fundamental mechanics of our civilisation. We, humans, are generally good at transforming energy. There is a body of historical and paleontological evidence that accurate adjustment of energy balance was one of the key factors in the evolutionary success of humans, both at the level of individual organisms and whole communities (Leonard, Robertson 1997[2]; Robson, Wood 2008[3]; Russon 2010[4])
When we talk about energy efficiency of the human civilisation, it is useful to investigate the way we consume energy. In this article, the question is being tackled by observing the pace of growth in energy efficiency, defined as GDP per unit of energy use (https://data.worldbank.org/indicator/EG.GDP.PUSE.KO.PP.KD?view=chart). The amount of value added we can generate out of a given set of production factors, when using one unit of energy, is an interesting metric. It shows energy efficiency as such, and, in the same time, the relative complexity of the technological basket we use. As stressed, for example, by Moreau and Vuille (2018[5]), when studying energy intensity, we need to keep in mind the threefold distinction between: a) direct consumption of energy b) transport c) energy embodied in goods and services.
One of the really deep questions one can ask about the energy intensity of our culture is to what extent it is being shaped by short-term economic fluctuations. Ziaei (2018[6]) proved empirically that observable changes in energy intensity of the U.S. economy are substantial, in response to changes in monetary policy. There is a correlation between the way that financial markets work and the consumption of energy. If the relative increase in energy consumption is greater than the pace of economic growth, GDP created with one unit of energy decreases, and vice versa. There is also a mechanism of reaction of the energy sector to public policies. In other words, some public policies have significant impact on the energy efficiency of the whole economy. Different sectors of the economy respond with different intensity, as for their consumption of energy, to public policies and to changes in financial markets. We can assume that a distinct sector of the economy corresponds to a distinct basket of technologies, and a distinct institutional outset.

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1 https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG

2 Leonard, W.R., and Robertson, M.L. (1997). Comparative primate energetics and hominoid evolution. Am. J. Phys. Anthropol. 102, 265–281.

3 Robson, S.L., and Wood, B. (2008). Hominin life history: reconstruction and evolution. J. Anat. 212, 394–425

4 Russon, A. E. (2010). Life history: the energy-efficient orangutan. Current Biology, 20(22), pp. 981- 983.

5 Moreau, V., & Vuille, F. (2018). Decoupling energy use and economic growth: Counter evidence from structural effects and embodied energy in trade. Applied Energy, 215, 54-62.

6 Ziaei, S. M. (2018). US interest rate spread and energy consumption by sector (Evidence of pre and post implementation of the Fed's LSAPs policy). Energy Reports, 4, 288-302.

Faisal et al. (2017[7]) found a long-run correlation between the consumption of energy and real output of the economy, studying the case of Belgium. Moreover, the same authors found significant causality from real output to energy consumption, and that causality seems to be uni-directional, without any significant, reciprocal loop.
Energy efficiency of national economies, as measured with the coefficient of GDP per unit of energy (e.g. per kg of oil equivalent), should take into account that any given market is a mix of goods – products and services – which generate aggregate output. Any combination "GDP <> energy use" is a combination of product markets, as well as technologies (Heun et al. 2018[8]). There is quite a fruitful path of research, which assumes that aggregate use of energy in an economy can be approached in a biological way, as a metabolic process. The MuSIASEM methodological framework seems to be promising in this respect (e.g. Andreoni 2017[9]). This leads to a further question: can changes in the aggregate use of energy be considered as adaptive changes in an organism, or in generations of organisms? In another development regarding the MuSIASEM framework, Velasco-Fernández et al (2018[10]) remind that real output per unit of energy consumption can increase, on a given basis of energy supply, through factors other than technological change towards greater efficiency in energy use. This leads to investigating the very nature of technological change at the aggregate level. Is aggregate technological change made only of engineering improvements at the microeconomic level, or maybe the financial reshuffling of the economic system counts, too, as adaptive technological change?
The MuSIASEM methodology stresses the fact that international trade, and its accompanying financial institutions, allow some countries to externalise industrial production, thus, apparently, to decarbonise their economies. Still, the industrial output they need takes place, just somewhere else.
From the methodological point of view, the MuSIASEM approach explores the compound nature of energy efficiency measured as GDP per unit of energy consumption. Energy intensity can be understood at least at two distinct levels: aggregate and sectoral. At the aggregate level, all the methodological caveats make the « GDP per kg of oil equivalent » just a comparative metric, devoid of much technological meaning. At the sectoral level, we get closer to technology strictly spoken.
There is empirical evidence that at the sectoral level, the consumption of energy per unit of aggregate output tends to: a) converge across different entities (regions, entrepreneurs etc.) b) tends to decrease (see for example: Yu et al. 2012[11]).

[7] Faisal, F., Tursoy, T., & Ercantan, O. (2017). The relationship between energy consumption and economic growth: Evidence from non-Granger causality test. Procedia Computer Science, 120, 671-675
[8] Heun, M. K., Owen, A., & Brockway, P. E. (2018). A physical supply-use table framework for energy analysis on the energy conversion chain. Applied Energy, 226, 1134-1162
[9] Andreoni, V. (2017). Energy Metabolism of 28 World Countries: A Multi-scale Integrated Analysis. Ecological Economics, 142, 56-69
[10] Velasco-Fernández, R., Giampietro, M., & Bukkens, S. G. (2018). Analyzing the energy performance of manufacturing across levels using the end-use matrix. Energy, 161, 559-572
[11] Yu, S., Wei, Y. M., Fan, J., Zhang, X., & Wang, K. (2012). Exploring the regional characteristics of inter-provincial CO2 emissions in China: An improved fuzzy clustering analysis based on particle swarm optimization. Applied energy, 92, 552-562

There is also empirical evidence that general aging of the population is associated with a lower energy intensity, and urbanization has an opposite effect, i.e. it is positively correlated with energy intensity (Liu et al. 2017[12])

It is important to understand, how and to what extent public policies can influence the energy efficiency at the macroeconomic scale. These policies can either address directly the issue of thermodynamic efficiency of the economy, or just aim at offshoring the most energy – intensive activities. Hardt et al. (2018[13]) study, in this respect, the case of United Kingdom, where each percentage of growth in real output has been accompanied, those last years, by a 0,57% reduction in energy consumption per capita.

There is grounds for claiming that increasing energy efficiency of national economies matters more for combatting climate change that the strictly spoken transition towards renewable energies (Weng, Zhang 2017[14]). Still, other research suggest that the transition towards renewable energies has an indirectly positive impact upon the overall energy efficiency: economies that make a relatively quick transition towards renewables seem to associate that shift with better efficiency in using energy for creating real output (Akalpler, Shingil 2017[15]).

It is to keep in mind that the energy efficiency of national economies has two layers, namely the efficiency of producing energy in itself, as distinct from the usage we make of the so-obtained net energy. This is the concept of Energy Return on Energy Invested (EROI), (see: Odum 1971[16]; Hall 1972[17]). Changes in energy efficiency can occur on both levels, and in this respect, the transition towards renewable sources of energy seems to bring more energy efficiency in that first layer, i.e. in the extraction of energy strictly spoken, as compared with fossil fuels. The problematically slow growth in energy efficiency could be coming precisely from the de-facto decreasing efficiency of transformation in fossil fuels (Sole et al. 2018[18]).

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[13] Hardt, L., Owen, A., Brockway, P., Heun, M. K., Barrett, J., Taylor, P. G., & Foxon, T. J. (2018). Untangling the drivers of energy reduction in the UK productive sectors: Efficiency or offshoring?. Applied Energy, 223, 124-133.

[14] Weng, Y., & Zhang, X. (2017). The role of energy efficiency improvement and energy substitution in achieving China's carbon intensity target. Energy Procedia, 142, 2786-2790.

[15] Akalpler, E., & Shingil, M. E. (2017). Statistical reasoning the link between energy demand, CO2 emissions and growth: Evidence from China. Procedia Computer Science, 120, 182-188.

[16] Odum, H.T. (1971) Environment, Power, and Society, Wiley, New York, NY, 1971.

[17] Hall, C.A.S., (1972) Migration and metabolism in a temperate stream ecosystem, Ecology, vol. 53 (1972), pp. 585 - 604.

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Technology and social structures are mutually entangled (Mumford 1964[19], McKenzie 1984[20], Kline and Pinch 1996[21]; David 1990[22], Vincenti 1994[23]; Mahoney 1988[24]; Ceruzzi 2005[25]). An excellent, recent piece of research by Taalbi (2017[26]) attempts a systematic, quantitative investigation of that entanglement.

The data published by the World Bank regarding energy use per capita in kg of oil equivalent (OEPC) (https://data.worldbank.org/indicator/EG.USE.PCAP.KG.OE) allows an interesting insight, when combined with structural information provided by the International Energy Agency (https://www.iea.org). As one ranks countries regarding their energy use per capita, the resulting hierarchy is, in the same time, a hierarchy in the broadly spoken socio-economic development. Countries displaying less than 200 kg of oil equivalent per capita are, in the same time, barely structured as economies, with little or no industry and transport infrastructure, with quasi-inexistent institutional orders, and with very limited access to electricity at the level of households and small businesses. In the class comprised between 200 kg OEPC and approximately 600 ÷ 650 kg OEPC, one can observe countries displaying progressively more and more development in their markets and infrastructures, whilst remaining quite imbalanced in their institutional sphere. Past the mark of 650 OEPC, stable institutions are observable. Interestingly, the officially recognised threshold of « middle income », as macroeconomic attribute of whole nations, seems corresponding to a threshold in energy use around 1 500 kg OEPC. The neighbourhood of those 1 500 kg OEPC looks like the transition zone between developing economies, and the emerging ones. This is the transition towards really stable markets, accompanied by well-structured industrial networks, as well as truly stable public sectors. Finally, as income per capita starts qualifying a country into the class of « developed economies », that country is most likely to pass another mark of energy consumption, that of 3000 kg OEPC. This stylized observation of how energy consumption is linked to social structures is partly corroborated by other research, e.g. that regarding social equality in the access to energy (see for example: Luan, Chen 2018[27])

The nexus of energy use per capita, on the one hand, and institutions on the other hand, has even found a general designation in recent literature: "energy justice". A cursory review of that

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[19] Mumford, L., 1964, Authoritarian and Democratic Technics, Technology and Culture, Vol. 5, No. 1 (Winter, 1964), pp. 1-8

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[23] Vincenti, W.G., 1994, The Retractable Airplane Landing Gear and the Northrop "Anomaly": Variation-Selection and the Shaping of Technology, Technology and Culture, Vol. 35, No. 1 (Jan., 1994), pp. 1-33

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[26] Taalbi, J. (2017). What drives innovation? Evidence from economic history. Research Policy, 46(8), 1437-1453.

[27] Duan, C., & Chen, B. (2018). Analysis of global energy consumption inequality by using Lorenz curve. Energy Procedia, 152, 750-755.

literature demonstrates the depth of emotional entanglement between energy and social structures: it seems to be more about the connection between energy and self-awareness of societies than about anything else (see for example: Fuller, McCauley 2016[28]; Broto et al. 2018[29]). The difficulty in getting rid of emotionally grounded stereotypes in this path of research might have its roots in the fact that we can hardly understand what energy really is, and attempts at this understanding send us to the very foundations of our understanding as for what reality is (Coelho 2009[30]; McKagan et al. 2012[31]; Frontali 2014[32]). Recent research, conducted from the point of view of management science reveal just as recent an emergence of new, virtually unprecedented, institutional patterns in the sourcing and the use of energy. A good example of that institutional change is to find in the new role of cities as active players in the design and implementation of technologies and infrastructures critical for energy efficiency (see for example: Geels et al. 2016[33]; Heiskanen et al. 2018[34]; Matschoss, Heiskanen 2018[35]).

Changes observable in the global economy, with respect to energy efficiency measured as GDP per unit of energy consumed, are interestingly accompanied by those in the supply of money, urbanization, as well as the shift towards renewable energies. Years 2008 – 2010, which marked, with a deep global recession, the passage towards currently experienced, record-long and record-calm period of economic growth, displayed a few other interesting transitions. In 2008, the supply of broad money in the global economy exceeded, for the first documented time, 100% of the global GDP, and that coefficient of monetization (i.e. the opposite of the velocity of money) has been growing ever since (World Bank 2018[36]). Similarly, the coefficient of urbanization, i.e. the share of urban population in the global total, exceeded 50% in 2008, and has kept growing since (World Bank 2018[37]). Even more intriguingly, the global financial crisis of 2007 – 2009 took place exactly when the global share of renewable energies in the total

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[35] Matschoss, K., & Heiskanen, E. (2018). Innovation intermediary challenging the energy incumbent: enactment of local socio-technical transition pathways by destabilization of regime rules. Technology Analysis & Strategic Management, 30(12), 1455-1469

[36] https://data.worldbank.org/indicator/FM.LBL.BMNY.GD.ZS last accessed November 25th, 2018

[37] https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS last accessed November 25th, 2018

consumption of energy was hitting a trough, below 17%, and as the global recovery started in 2010, that coefficient started swelling as well, and has been displaying good growth since then[38]. Besides, empirical data indicates that since 2008, the share of aggregate amortization (of fixed assets) in the global GDP has been consistently growing, after having passed the cap of 15% (Feenstra et al. 2015[39]). Some sort of para-organic pattern emerges out of those observations, where energy efficiency of the global economy is being achieved through more intense a pace of technological change, in the presence of money acting as a hormone, catabolizing real output and fixed assets, whilst anabolizing new generations of technologies.

The model

In the spirit of the MuSIASEM methodology, it is assumed that human social structures are metabolic systems, which feed on non-edible energies, consumable through a set of technologies TC. Technologies in the set TC are katabolic regarding the primary sources of energy, whilst they are anabolic regarding products, services and durable structures (i.e. infrastructure, constructed real estate etc.). The concept of technology used here is quite broad, and covers the behavioural component as well, i.e. the know-how, human skills, formalized cultural content etc. There is a certain amount of energy that a given population needs to: a) sustain itself b) achieve a certain level of socio-economic development. Further, it is assumed that the overall level of socio-economic development finds a cornerstone in the coefficient of real output per capita (Q/N), accompanied by additional utilities U (e.g. infrastructure, healthcare etc.) and institutions (i.e. stable legal and constitutional system etc.). It can be argued that utilities and institutions need both a tax base, and a corresponding level of income per capita. On the grounds of these assumptions, as well as of distinctions named in the introduction, two hypotheses are being formulated, for empirical check:

- **Hypothesis #1**: Energy efficiency of national economies (GDP per unit of energy consumed) is weakly correlated with their energy intensity (Energy per capita) and strongly correlated with their overall level of socio-economic development (GDP per capita).

- **Hypothesis #2**: Structural characteristics of national economies, namely their individual degrees of monetization, urbanization, and their pace of technological change, are strongly correlated with their energy efficiency (GDP per unit of energy consumed).

In order to check those hypotheses, and explore their context, a model is being formulated, where energy efficiency of economic systems, observable as the coefficient of GDP per unit of energy consumed ($^{Q}/_{E}$) is based on the functional connection between the capacity of a given system to generate compound real output of goods and services, on the one hand, and the energy required to produce each particular good and service encompassed in that compound real output. The functional connection in question consists of two complex sets: that of technologies, and

[38] https://data.worldbank.org/indicator/EG.FEC.RNEW.ZS last accessed November 25th, 2018

[39] Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at www.ggdc.net/pwt

that of trade flows with other economic systems, both characterized, precisely, by a proportion between the output of goods and service, and the input of energy.
Consistently with the literature introduced above, and with author's previous research (Wasniewski 2017a[40], Wasniewski 2017b[41]) the basic model built for the purposes of empirical research assumes that the energy efficiency of national economies is significantly influenced by their strictly structural characteristics, i.e. by proportions between flows and balances in four main fields: the pace of technological change, the monetary system, the relative shift towards renewable energies, and the degree of urbanization. The pace of technological change is assumed to be observable as the proportion between aggregate amortization of fixed assets, and the real output of the economy. This structural coefficient, possible to express as a strict fraction, reflects the percentage of proceedings from real output that need to be reallocated into the maintenance of technological competitiveness. As regards the monetary system, the essential proportion referred to in the model is that between the aggregate supply of money, and real output. A residual constant of energy efficiency is supposed to be manifest in the presence of these structural factors. Equation (1) sums up this basic approach.

$$\frac{Q}{E} = a_1\frac{A}{Q} + a_2\frac{M}{Q} + a_3\frac{RE}{E} + a_4\frac{UN}{N} + b \qquad (1)$$

… where $\frac{Q}{E}$ is the coefficient of GDP (real output) per unit of energy consumed, $\frac{A}{Q}$ represents the ratio of aggregate amortization in fixed assets denominated in units of real output, the ratio $\frac{M}{Q}$ represents the share of money supply in the aggregate output (i.e. the opposite of the velocity of money) , $\frac{RE}{E}$ is the share of renewable energies in the final consumption of energy, and $\frac{UN}{N}$ stands for the share of urban population in the total population. All these four structural variables are fractions strictly spoken, i.e. they can be directly expressed as percentages of their respective denominators.

The basic model has two mutations, corresponding to different types of scale factors. The type labelled further as 'weak scale factors' encompasses variables, which are coefficients of intensity, i.e. proportions denominated in absolute amounts instead of being denominated as fractions strictly spoken. They are: a) the coefficient of the number of domestic patent applications per 1000 000 inhabitants ($\frac{PatApp}{N}$) b) the coefficient of final energy consumption per capita ($\frac{E}{N}$) and c) the coefficient of real output per capita ($\frac{Q}{N}$) . Equation (2) represents formally this mutation of the basic model.

$$\frac{Q}{E} = a_1\frac{A}{Q} + a_2\frac{M}{Q} + a_3\frac{RE}{E} + a_4\frac{UN}{N} + a_5\frac{PatApp}{N} + a_6\frac{E}{N} + a_7\frac{Q}{N} + b \qquad (2)$$

[40] Wasniewski, K., (2017), Financial Equilibrium in the Presence of Technological Change, Journal of Economics Library, Volume 4 (2), June 20, s. 160 – 171, KSP Journals, Turkey, 2017
[41] Wasniewski, K., (2017), Technological change as intelligent, energy-maximizing adaptation, Journal of Economic and Social Thought, Volume 4 September 3, 263-276, Turkey, 2017

The model containing weak scale factors reflects the general assumption that the more intense are the corresponding processes – patentable research, final consumption of energy and production of real output – in relation to the headcount of the population, the greater is the energy efficiency of the national economy. Besides, the weak scale factors are supposed to compensate distortions observable in the empirical distribution of structural variables $\frac{M}{Q}$ and $\frac{RE}{E}$. The $\frac{M}{Q}$ tends to vary strongly in the cross-sectional dimension, without clear connection with the efficiency of technological base observable in a given country. The share of renewable energies in the overall energy consumption ($\frac{RE}{E}$) is subject to a distortion due to the formal definition of renewables. Biofuels are technically categorized as renewable sources of energy, and they make a substantial share of energy-sourcing in the poorest countries of the globe, yet that local, strong reliance on the burning of vegetal remains is not a proof of technological advancement. On the contrary, these are the least developed technological environments.

Another mutation of the basic model, containing the so-called strong scale factors, aims at capturing the impact of the sheer scale in national economies upon their respective energy efficiencies. Population (N) and real output (Q) are introduced into the basic model, supplanting the previously mentioned intensities, as shown in equation (3).

$$\frac{Q}{E} = a_1\frac{A}{Q} + a_2\frac{M}{Q} + a_3\frac{RE}{E} + a_4\frac{UN}{N} + a_8N + a_9Q + b \qquad (3)$$

The dataset and the method of its analysis

A compound database has been created for the purposes of this research, covering the period since 1990 through 2014, as regards 161 countries. Penn Tables 9.0 (Feenstra et al. 2015[42]) have been used for measuring the empirical values of real output, population, and that of aggregate amortization of fixed assets. Data regarding energy efficiency, the share of renewables in the final consumption of energy, as well as that regarding money supply and R&D activity has been sourced from the database publicly available with the World Bank[43].

The raw data has been transformed at three levels, so as to account for the possible non-stationarity, and for the differences in the respective scales of measurement. Firstly, natural logarithms have been taken out of empirical values, so as to level the short-term fluctuations. Secondly, the component of long-term trend has been extracted from each series of data, by taking its local exponential coefficient $cl = \frac{\ln(x)}{t-1889}$, where *x* is the local value of the observed variable, and *t* is the associated year, in the range 1990 – 2014. The « *cl* » transformation assumes that each variable under scrutiny contains a component of secular, possibly endogenous change in an exponential progression $x = e^{t*cl}$.

[42] Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at www.ggdc.net/pwt

[43] https://data.worldbank.org last accessed November 25th, 2018

Thirdly, a short-term trend is extracted, by computing local exponential coefficients $cs = \frac{\ln(x)}{t-1989}$, with the same assumptions regarding *x* and *t*, in an exponential process of the $x = e^{t*cs}$ type. This time, it is assumed that each variable studied contains a component of short-term, endogenous change, whose starting point is 1990, thus the first year of observation. Given the arithmetical structure of the « cs » transformation (the local natural logarithm being denominated over a quickly increasing value: 1, 2, 3 etc.), it simulates a hypothetical situation when 1990 is like a 'big bang', regarding the phenomena observed, and this initial quake spreads ripples over time, with decreasing force. This particular transformation – the '*cs*' one – attempts to explore the general intuition, expressed in research on the history of technology, that technological progress occurs in leaps and jumps rather than along calmly incremental trends (see for example: David 1990[44]; Vincenti 1994[45]; Edgerton 2011[46];)

The usage of exponential coefficients to estimate the local pace of change has some grounds in literature. Models based on natural logarithms, such as the Logarithmic Mean Divisia Index (LDMI) are commonly used, and proven meaningful, in research on energy efficiency (see: Hoekstra R, van den Bergh 2003[47]; Ang 2004[48]; Su & Ang 2012[49]; Hardt et al. 2018[50]). The here-presented method is a variation in the use of natural logarithms: instead of just considering them as less biased a form of original, raw observations, it is possible to go one step further and assume that natural logarithms are local paces of change in hypothetically existing, exponentially changing processes marked by hysteresis.

Why observing local paces of change instead of normalized observations? The previously cited research by Akalpler & Shingil (2017[51]) suggests that as regards energy efficiency, local anomalies (i.e. out-of-normal changes) can have bigger an impact than normalized trends.

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[44] David, P. A. (1990). The dynamo and the computer: an historical perspective on the modern productivity paradox. The American Economic Review, 80(2), 355-361.

[45] Vincenti, W.G., 1994, The Retractable Airplane Landing Gear and the Northrop "Anomaly": Variation-Selection and the Shaping of Technology, Technology and Culture, Vol. 35, No. 1 (Jan., 1994), pp. 1-33

[46] Edgerton, D. (2011). Shock of the old: Technology and global history since 1900. Profile books

[47] Hoekstra R, van den Bergh JCJM. (2003), Comparing structural and index decomposition analysis, Energy Economics 2003, vol. 25, pp. 39–64, http://dx.doi.org/10.1016/S0140-9883(02) 00059-2

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[49] Su B, Ang BW., (2012), Structural decomposition analysis applied to energy and emissions: Some methodological developments, Energy Economics 2012, vol. 34, pp. 177–88. http://dx.doi. org/10.1016/j.eneco.2011.10.009.

[50] Hardt, L., Owen, A., Brockway, P., Heun, M. K., Barrett, J., Taylor, P. G., & Foxon, T. J. (2018). Untangling the drivers of energy reduction in the UK productive sectors: Efficiency or offshoring?. Applied Energy, 223, 124-133.

[51] Akalpler, E., & Shingil, M. E. (2017). Statistical reasoning the link between energy demand, CO2 emissions and growth: Evidence from China. Procedia Computer Science, 120, 182-188.

For the sake of presentational convenience, these three types of transformed data are further labelled as, respectively, '*ln*' (natural logarithms), '*cl*' (long-term trend), and '*cs*' (short-term trend).
The method of empirical testing regarding the model presented unfolds in six steps, and within each step, three types of transformed data – namely '*ln*', '*cl*', and '*cs*' – are used in sequence. Step I consists in taking the basic model, as expressed in equation (1), and testing it with the assumption of random effects at the level of countries (i.e. without any special reserves as for national idiosyncrasies). Structural variables from equation (1) are expressed as percentages. In this step, as well as in the following ones, models are tested using Ordinary Least Squares linear regression, with Wizard for MacOS as analytical software. In Step II, fixed effects at the level of countries are assumed, in the same model. Steps III and IV mark the passage to testing equation (2), with weak scale effects, respectively with random and fixed country-effects. Finally, in steps V and VI the same is done with equation (3), thus with strong scale factors.

Results of empirical tests

Empirical research, summarized in the previous section, offers, in the first place, a wealth of alternative methodological approaches to the same problem, namely the mechanics of change in the energy efficiency of national economies, as measured with the coefficient of GDP per unit of energy consumed. Three models are tested – purely structural, structural with intensities, and structural with strong factors of scale – whilst introducing into each of them the possibility of fixed national effects, as well as alternative types of process under scrutiny, i.e. stationary variation, long-term trend, and short-term explosive change starting in 1990.
Given that multitude of angles, the first conclusions are methodological. When taking into account two metrics of empirical accuracy – the R^2 coefficient of capturing the overall variance of energy efficiency, and the robustness of individual correlations as given by the *p*-value – the model including **structural variables and weak factors of scale (intensities)** seems to offer the most explanatory power. The other two models are far weaker in that respect. As we pass to the type of process observed in that strongest model, the hypothesis of short-term explosive change starting in 1990, and sending ripples into the next 23 years, comes as the most meaningful. We are talking here about the raw observations being transformed into local coefficients of an exponential progression of the $x = e^{t*cs}$ type, thus into $cs = \frac{\ln(x)}{1-1989}$. When shifting to the observation of the long-term trend, thus to local exponential coefficients computed with the assumption that the corresponding progression started in 1889, the overall explanatory power of the model falls significantly, mostly due to lower a robustness of local correlations. With the assumption of stationary oscillation in the variables studied, thus when taking into account just their natural logarithms, explanatory power is even lower.
Whatever the type of process studied – stationary, long trend or the short explosive one – the inclusion of fixed effects in individual, national economies takes a lot of explanatory power away rather than adds thereof. Whilst offering a higher determination in the explained variable (i.e. higher an R^2), fixed effects translate into largely random correlations, as measured with the *p*-value. It can be cautiously assumed that national idiosyncrasies have much less importance than global, overarching changes in time.
The methodological conclusions summarized above allow to sketch a general context for studying the relative impact of explanatory factors upon the energy efficiency of national economies. We are focusing on the model encompassing the purely structural variables – share of aggregate amortization, as well as of money supply in real output, urbanization and relative orientation towards renewable energies – in the presence of weak scale factors, namely energy

intensity, patenting activity and GDP per capita. Inside that theoretical framework, the process which seemingly conveys the most robust insight is that of short-term pace of change, with a hypothetical 'big bang' in 1990, and its decreasing secondary quakes over time, through 2014, thus the process observable through the '***cs***' transformation of raw data. The relatively highest explanatory power of this particular approach to empirical observations, i.e. as manifestations of explosive, sudden change, indirectly corroborates claims, cited in the introduction, about technological change being rather turbulent than linearly even. Random effects are assumed at the country level, i.e. individual specificities of each country under scrutiny are assumed to be of secondary importance. Hence, detailed results of the corresponding regression are showed in the table below, whilst the overall results of all the tests are presented in the Appendix, at the end of this article.

Table 1

Explained variable: $cs(Q/E)$, **N = 1 228; R^2 = 0,983**				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cs(A/Q)$	0,217	0,152	1,432	0,152
$cs(M/Q)$	0,142	0,056	2,525	0,012
$cs\ (RE/E)$	-0,03	0,012	-2,458	0,014
$cs(UN/N)$	0,587	0,142	4,136	0,001
$cs(PatApp/N)$	-0,085	0,017	-5,024	0,001
$cs(E/N)$	-0,785	0,062	-12,733	0,001
$cs(Q/N)$	0,621	0,091	6,8	0,001
The constant term	-0,009	0,003	-3,604	0,001

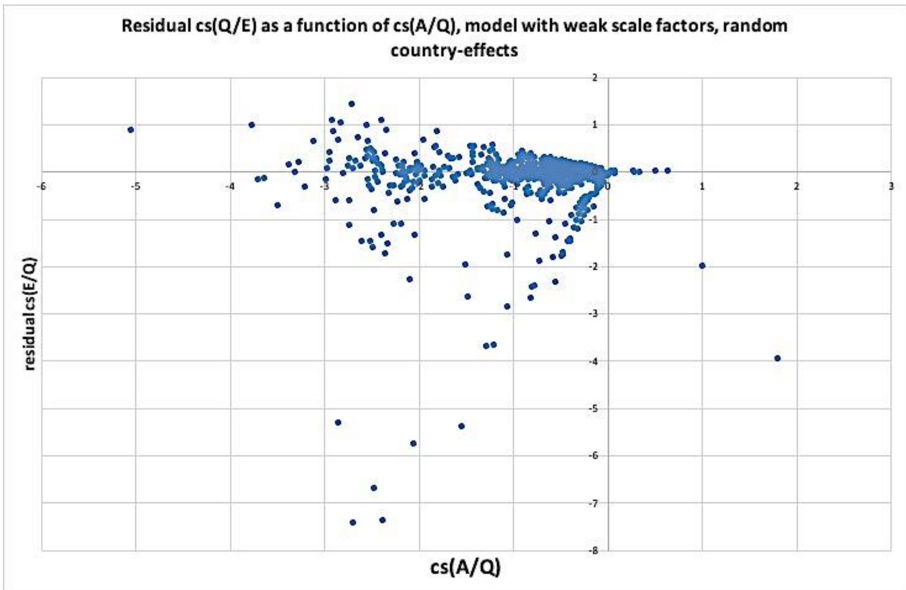
Source: author's

With that methodological frame in mind, we can pass to studying the relative importance of particular variables. This time, as it is all about one model and one type of data, thus with the same, high R^2 = 0,983, the aforementioned importance relies both on the magnitude of the regression coefficient, and on the robustness of the corresponding correlation, as measured with the *p*-value. What comes to the very foreground is the tension between ***cs(E/N)***, with a significantly negative coefficient, on the one hand, and ***cs(Q/N)*** combined with ***cs(UN/N)*** on the other hand, with their strongly positive coefficients. The faster the short-term pace of change in energy consumption per capita, the slower the pace of change in GDP per unit of energy consumed - this fact alone is not really a surprise. Still, what comes as one is the opposition in signs between ***cs(E/N)***, with a negative coefficient, and ***cs(Q/N)***, which, together with ***cs(UN/N)*** bear positive signs in their coefficients. Within the scope of observation, as the pace of growth in energy intensity ramps up, urbanization and economic development seem to slow down, and vice versa. This, in turn, suggests some sort of developmental cycle, where energy intensity grows quickly, in the first place, and then its speed subsides, to give room for grounding the gains: development of urban settlements, and that of markets for goods and services. When these two exhaust the previously developed energy base, the cycle starts over again.

The next variable in line, in terms of explanatory power in this particular model, is the coefficient of monetization, as the opposite of the velocity of money. It is the *cs(M/Q)*, or the short-term exponential change in the proportion between the supply of money, and real output. Whilst endowed with a substantial coefficient of regression, *cs(M/Q)* seems to convey a little more aleatory changes than the previously mentioned three variables. Generally, the higher the

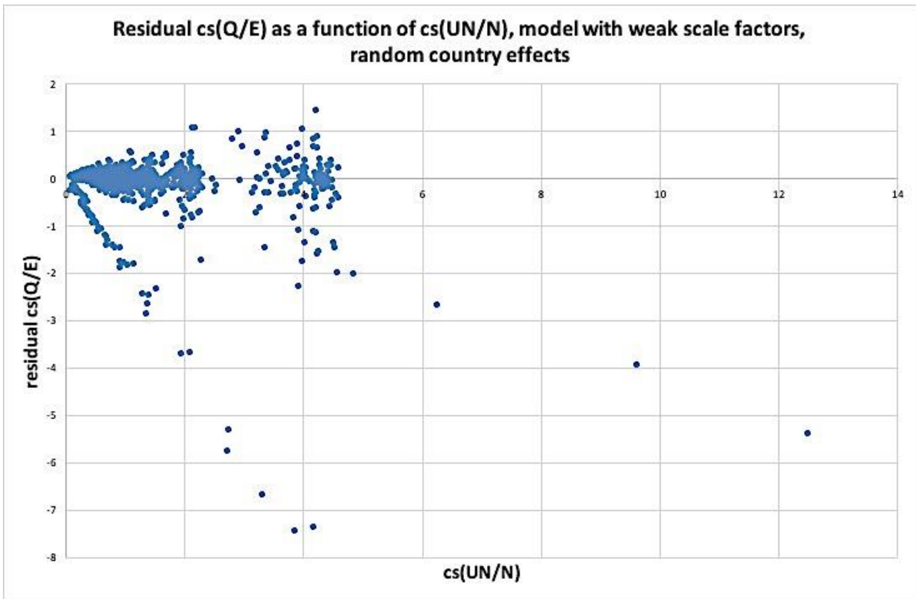
pace of growth in monetization, the higher the corresponding rate of growth in ***(E/Q)***, or energy efficiency in national economies. This corroborates other research, cited in the introduction. As we are talking about random effects at the country level, national idiosyncrasies in financial markets seem to have little significance.
Given both the magnitude of the regression coefficient, and the significance of the correlation, the share of renewables seems to have little impact on the energy efficiency of national economies. That seems consistent with the reservations expressed earlier as for the actual denotation of this variable.
The pace of technological progress, in this particular model, is captured at two levels: the input of patentable invention, or *cs(PatApp/N)*, and the relative burden of aggregate amortization upon real output, or *cs(A/Q)*. The former has an apparently secondary, negative, and statistically significant an impact on the pace of change in energy efficiency, or *cs(Q/N)*. The latter has one order of magnitude more in its coefficient, as well as a positive sign, and a noticeable amount of random variance (p = 0,152). The speed that business people have to amortize their technologies at seems to have a bit of 'butterfly's wings' syndrome in it: it has an impact, but this impact contains a portion of unpredictable.
All the long of the methodology used in this research, the robustness of correlations, as measured with the p-value, is considered as an important criterion of explanatory power. Consistently with this approach, it is worth studying the residuals of local '***cs***' coefficients of exponential growth (thus coefficients of short-run, explosive change), generated by the model with weak scale factors and random effects at the country level. Graphs 1 – 5 show the spatial distribution of residuals in ***cs(Q/E)***, thus in the short-term coefficient of exponential growth in energy efficiency, over the span of local '***cs***' coefficients in main explanatory variables.

Graph 1



Source: author's

Graph 2

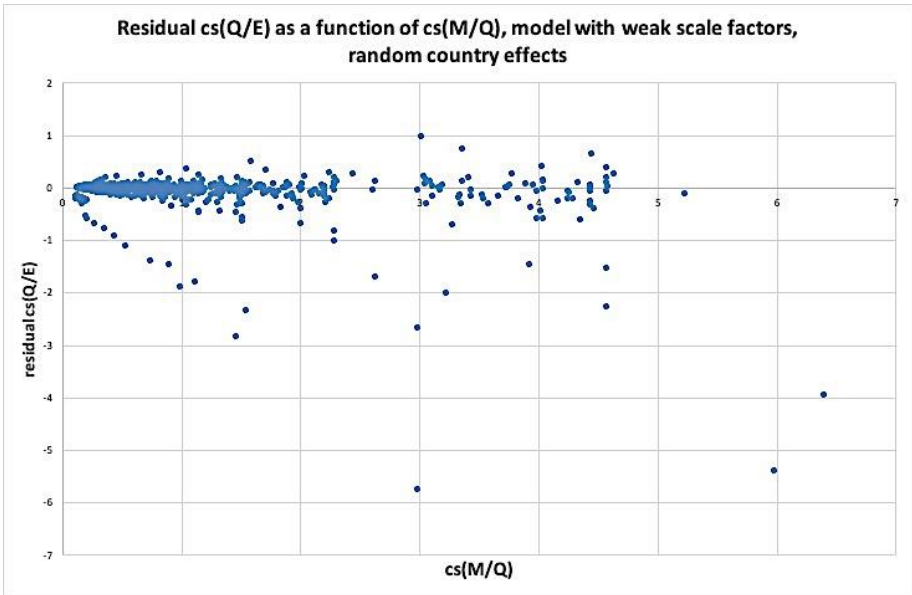


Source: author's

The residuals of ***cs(Q/E)*** over the actually observable span of ***cs(A/Q)*** – thus the explanatory variable endowed with the least robust correlation - are distributed in almost exactly the opposite way to the distributions of residuals obtained over the other variables, more robust in their correlations. The greatest discrepancies between the predicted values of ***cs(Q/E)*** and the actual ones are to notice at the relatively low values of ***cs(A/Q)***, de facto at the negative ones, i.e. in countries and years where and when the share of aggregate amortization in real output was decreasing, and thus the pace of technological change was slowing down. In cases of real acceleration in technological change, the accuracy of prediction regarding ***cs(Q/E)*** increases dramatically. As regards the distribution of residuals over the other explanatory variables, it takes the form of fan spreading from left to right: the accuracy of prediction decreases as the values of those variables increase.

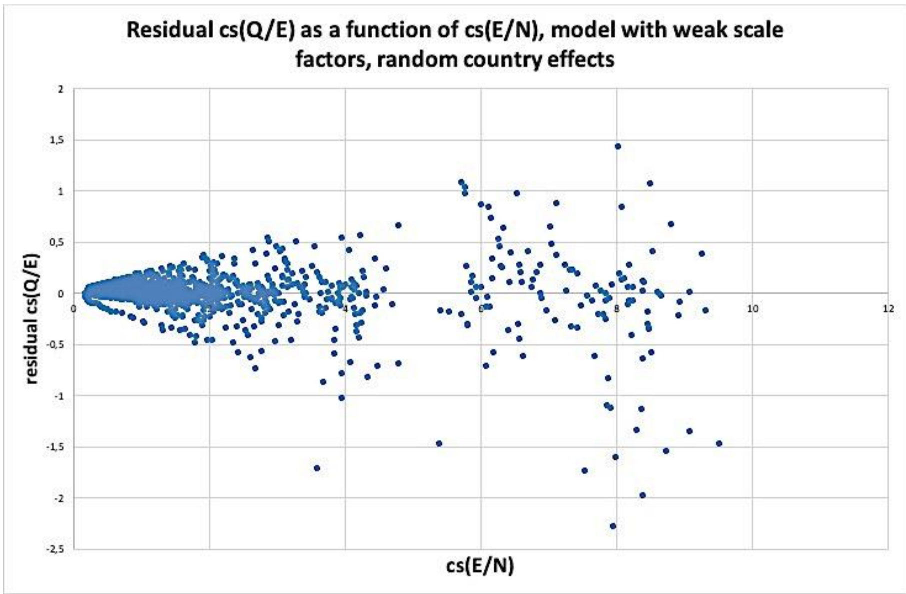
On the whole, the relatively low robustness of correlation between ***cs(A/Q)*** and ***cs(Q/E)*** seems to be stemming from the idiosyncratic distribution of the former in the sample. The share of aggregate amortization in real output is the only variable in this model, which in some cases takes negative '***cs***' coefficients. An even closer look at this variable shows a pattern in time rather than in space: during the years 1990 – 1997, the A/Q coefficient had been systematically decreasing, to come to a virtual standstill between 1997 and 2004, and to take off, on an ascending path, since 2005 through 2014.

Graph 3



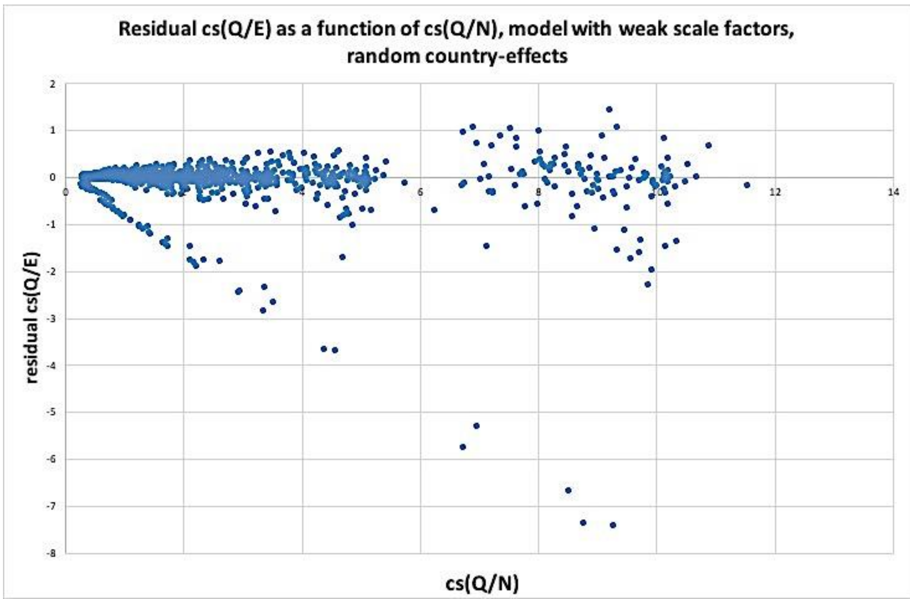
Source: author's

Graph 4



Source: author's

Graph 5



Source: author's

Conclusions

This paper attempts at exploring the factors of change in the so-called energy efficiency of economic systems, i.e. in their capacity to generate real output from a given energy base. Probably the most significant insight that comes out of the above-introduced empirical research regards the methodology of such research. Quite unexpectedly for the author, a specific transformation of raw data, labelled here as '*cs*', brings the most explanatory power. Slightly an artificial situation is created, when the first year of observation, in the dataset (here: 1990) is considered as the first unit of time after a hypothetical deep shock, and that shock is supposed to send progressively weakening an echo into the subsequent years. It is being mathematically expressed as an exponential progression of the $x = e^{t*cs}$ type, where $cs = \frac{\ln(x)}{t-1989}$. It might be an indirect proof that apprehending technological and economic change as explosive and turbulent, rather than secularly linear, is cognitively fruitful. It is to notice that such type of transformation can be introduced in virtually any type of chronological data, and it is to wonder how it can change the insights from said data.

As regards the hypotheses formulated as the basis of the analytical model, their empirical check brings nuances and shades. **Hypothesis #1**, stating that energy efficiency of national economies (GDP per unit of energy consumed) is weakly correlated with their energy intensity (Energy per capita) and strongly correlated with their overall level of socio-economic development (GDP per capita), proves just partially true. Whatever the type of transformation in raw observations, energy intensity is strongly correlated with energy efficiency, and this is a negative correlation. Sharp increase in energy intensity of an economic system can be mostly observed in developing countries, as they break the successive glass ceilings of socio-economic development. Those leaps in the energy base, taken alone, seem being counter-productive for the capacity to generate real output from said energy base, yet they seem to trigger a longer-run process, which, in turn, generates improvement in energy efficiency. In other words, hypothesis #1, when checked empirically, describes a sequence of development. Firstly, we increase the overall intake of energy by the social structure, and then we build an even more far-reaching increase in energy efficiency.

Hypothesis #2, claiming that structural characteristics of national economies, namely their individual degrees of monetization, urbanization, and their pace of technological change, are strongly correlated with their energy efficiency (GDP per unit of energy consumed), seems to be generally true. At this point, the author finds it important to stress a distinction as for the interpretation of monetary factors. Some researchers, mentioned in the introduction, especially those following the MuSIASEM methodology, seem considering monetary factors as somehow artificial and distortive, regarding the 'real' change in energy efficiency. The author of this article holds a different view: the most logical understanding of monetary systems seems to an analogy to endocrine systems, with money being a hormone that catabolizes excesses of liquidity in one place and anabolizes man-made resources in other places. Thus, the relatively high importance of monetary supply, measured as the share of broad money in real output, and quite significant in the empirical results brought forth in this paper, is to be interpreted as quite high a degree of endocrine excitement in the national economies studied, rather than as a disturbance to 'real stuff'.

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Appendix – detailed results of regression tests

The basic model based on structural variables

Table 2

Explained variable: $\ln(Q/E)$, N = 1 949 ; R^2 = 0,145				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\ln(A/Q)$	0,199	0,033	6,058	0,001
$\ln(M/Q)$	0,145	0,021	6,75	0,001
$\ln(RE/E)$	-0,015	0,006	-2,52	0,012
$\ln(UN/N)$	-0,002	0,011	-0,173	0,862
The constant term	1,873	0,136	13,724	0,001

Source: author's

Table 3

Explained variable: $cl(Q/E)$, N = 1 954 ; R^2 = 0,114				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cl(A/Q)$	0,117	0,026	4,419	0,001
$cl(M/Q)$	0,132	0,022	6,101	0,001
$cl(RE/E)$	-0,02	0,006	-3,278	0,001
$cl(UN/N)$	0,028	0,012	2,247	0,025
The constant term	0,015	0,001	14,358	0,001

Source: author's

Table 4

Explained variable: $cs(Q/E)$, N = 1 949; R^2 = 0,888				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cs(A/Q)$	-0,148	0,049	-3,023	0,003
$cs(M/Q)$	0,297	0,083	3,553	0,001
$cs(RE/E)$	-0,015	0,02	-0,772	0,440
$cs(UN/N)$	0,109	0,079	1,375	0,169
The constant term	0,007	0,006	1,248	0,212

Source: author's

The model based on structural variables, with fixed effects

Table 5

Explained variable: $\ln(Q/E)$, N = 1 949 ; R^2 = 0,912				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\ln(A/Q)$	0,128	0,496	0,258	0,796
$\ln(M/Q)$	0,166	0,05	3,347	0,001
$\ln(RE/E)$	0,165	0,269	0,613	0,540
$\ln(UN/N)$	0,284	2,415	0,117	0,907

Source: author's

Table 6

Explained variable: $cl(Q/E)$, N = 1 954; R^2 = 0,897				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cl(A/Q)$	0,077	0,146	0,524	0,600
$cl(M/Q)$	0,036	0,206	0,177	0,859
$cl(RE/E)$	0,144	0,095	1,522	0,128
$cl(UN/N)$	0,104	0,36	0,288	0,773

Source: author's

Table 7

Explained variable: $cs(Q/E)$, N = 1 949; R^2 = 0,925				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cs(A/Q)$	-0,145	0,066	-2,182	0,029
$cs(M/Q)$	0,277	0,114	2,436	0,015
$cs(RE/E)$	-0,01	0,027	-0,388	0,698
$cs(UN/N)$	0,128	0,112	1,142	0,254

Source: author's

The model with weak scale effects per capita – energy consumption, income and patent activity

Table 8

Explained variable: $\ln(Q/E)$, N = 1 228 ; R^2 = 0,848				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\ln(A/Q)$	-0,026	0,025	-1,064	0,287
$\ln(M/Q)$	0,01	0,016	0,597	0,551
$\ln(RE/E)$	-0,024	0,004	-5,487	0,001

$\ln(UN/N)$	0,087	0,031	2,831	0,005
$\ln(PatApp/N)$	-0,058	0,005	-12,33	0,001
$\ln(E/N)$	-0,857	0,018	-47,234	0,001
$\ln(Q/N)$	0,881	0,025	34,87	0,001
The constant term	-0,015	0,106	-0,142	0,887

Source: author's

Table 9

Explained variable: $cl(Q/E)$, N = 1 228 ; R^2 = 0,839				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cl(A/Q)$	-0,037	0,024	-1,534	0,125
$cl(M/Q)$	0,038	0,017	2,202	0,028
$cl(RE/E)$	-0,021	0,004	-4,937	0,001
$cl(UN/N)$	0,163	0,032	5,036	0,001
$cl(PatApp/N)$	-0,068	0,004	-15,16	0,001
$cl(E/N)$	-0,867	0,019	-45,625	0,001
$cl(Q/N)$	0,902	0,027	33,966	0,001
The constant term	-0,005	0,001	-7,765	0,001

Source: author's

Table 10

Explained variable: $cs(Q/E)$, N = 1 228; R^2 = 0,983				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cs(A/Q)$	0,217	0,152	1,432	0,152
$cs(M/Q)$	0,142	0,056	2,525	0,012
$cs\ (RE/E)$	-0,03	0,012	-2,458	0,014
$cs(UN/N)$	0,587	0,142	4,136	0,001
$cs(PatApp/N)$	-0,085	0,017	-5,024	0,001
$cs(E/N)$	-0,785	0,062	-12,733	0,001
$cs(Q/N)$	0,621	0,091	6,8	0,001
The constant term	-0,009	0,003	-3,604	0,001

Source: author'

The model with weak scale effects per capita – energy consumption, income and patent activity – and fixed effects

Table 11

Explained variable: $\ln(Q/E)$, N = 1 228; R^2 = 0,960				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\ln(A/Q)$	-0,047	0,773	-0,061	0,951
$\ln(M/Q)$	0,109	0,211	0,517	0,605
$\ln(RE/E)$	0,038	0,343	0,111	0,912
$\ln(UN/N)$	0,296	5,047	0,059	0,953
$\ln(PatApp/N)$	-0,018	0,265	-0,069	0,945
$\ln(E/N)$	-0,728	1,358	-0,536	0,592
$\ln(Q/N)$	0,526	0,284	1,852	0,064

Source: author's

Table 12

Explained variable: $cl(Q/E)$, N = 1 228 ; R^2 = 0,951				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cl(A/Q)$	-0,058	0,191	-0,303	0,762
$cl(M/Q)$	0,124	0,19	0,654	0,513
$cl(RE/E)$	0,008	0,078	0,098	0,922
$cl(UN/N)$	0,522	0,398	1,309	0,191
$cl(PatApp/N)$	-0,036	0,03	-1,199	0,231
$cl(E/N)$	-0,741	0,41	-1,809	0,071
$cl(Q/N)$	0,529	0,445	1,187	0,235

Source: author's

Table 13

Explained variable: $cs(Q/E)$, N = 1 228 ; R^2 = 0,988				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cs(A/Q)$	0,287	0,179	1,601	0,110
$cs(M/Q)$	0,183	0,064	2,862	0,004
$cs\ (RE/E)$	-0,029	0,016	-1,804	0,072
$cs(UN/N)$	0,738	0,167	4,433	0,001
$cs(PatApp/N)$	-0,092	0,021	-4,285	0,001
$cs(E/N)$	-0,768	0,071	-10,75	0,001
$cs(Q/N)$	0,541	0,094	5,742	0,001

Source: author's

The model with strong scale effects – GDP and population

Table 14

Explained variable: $\ln(Q/E)$, N = 1 916 ; R^2 = 0,293				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\ln(A/Q)$	0,148	0,035	4,226	0,001
$\ln(M/Q)$	0,031	0,022	1,391	0,164
$\ln(RE/E)$	0,056	0,007	7,81	0,001
$\ln(UN/N)$	0,342	0,048	7,142	0,001
$\ln(Q)$	0,116	0,02	5,789	0,001
$\ln(N)$	-0,116	0,02	-5,708	0,001
The constant term	1,167	0,274	4,257	0,001

Source: author's

Table 15

Explained variable: $cl(Q/E)$, N = 1 921 ; R^2 = 0,256				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cl(A/Q)$	0,11	0,037	2,971	0,003
$cl(M/Q)$	0,015	0,025	0,593	0,553
$cl(RE/E)$	0,053	0,008	6,787	0,001
$cl(UN/N)$	0,378	0,035	10,812	0,001
$cl(Q)$	0,11	0,017	6,311	0,001
$cl(N)$	-0,101	0,015	-6,642	0,001
The constant term	0,008	0,001	5,607	0,001

Source: author's

Table 16

Explained variable: $cs(Q/E)$, N = 1 916 ; R^2 = 0,923				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$cs(A/Q)$	0,193	0,104	1,855	0,064
$cs(M/Q)$	0,016	0,058	0,273	0,785
$cs\ (RE/E)$	0,026	0,025	1,021	0,307
$cs(UN/N)$	0,602	0,076	7,93	0,001
$cs(Q)$	-0,032	0,044	-0,709	0,478
$cs(N)$	0,013	0,035	0,365	0,715
The constant term	-0,005	0,004	-1,107	0,269

Source: author's

The model with strong scale effects – GDP and population – and fixed effects

Table 17

Explained variable: $\ln(Q/E)$, N = 1 916; R^2 = 0,940				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\ln(A/Q)$	0,073	0,666	0,109	0,913
$\ln(M/Q)$	0,039	0,398	0,098	0,922
$\ln(RE/E)$	0,158	0,437	0,361	0,718
$\ln(UN/N)$	-0,245	1,342	-0,182	0,855
$\ln(Q)$	0,366	0,848	0,432	0,666
$\ln(N)$	-0,437	5,645	-0,077	0,938

Source: author's

Table 18

Explained variable: $\text{cl}(Q/E)$, N = 1 921; R^2 = 0,911				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\text{cl}(A/Q)$	0,013	0,108	0,121	0,904
$\text{cl}(M/Q)$	0,017	0,185	0,093	0,926
$\text{cl}(RE/E)$	0,216	0,13	1,666	0,096
$\text{cl}(UN/N)$	0,138	0,539	0,256	0,798
$\text{cl}(Q)$	0,294	0,289	1,017	0,309
$\text{cl}(N)$	-0,169	0,151	-1,116	0,265

Source: author's

Table 19

Explained variable: $\text{cs}(Q/E)$, N = 1 916; R^2 = 0,948				
Explanatory variable	***Coefficient of regression***	***Robust standard error***	***t-statistic***	***p-value***
$\text{cs}(A/Q)$	0,186	0,116	1,6	0,110
$\text{cs}(M/Q)$	-0,003	0,072	-0,043	0,966
$cs\ (RE/E)$	0,024	0,034	0,709	0,478
$\text{cs}(UN/N)$	0,612	0,097	6,283	0,001
$\text{cs}(Q)$	-0,042	0,06	-0,699	0,485
$\text{cs}(N)$	0,021	0,047	0,447	0,655

Source: author's