Technological Change as Intelligent, Energy-Maximizing Adaptation

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Abstract
The picture of technological change over the last 70 years in the global economy is ambiguous, with two salient facts: Total Factor Productivity has been systematically falling since 1979, whilst the average global food deficit has been systematically declining since 1992. Building upon those two fundamental facts, this article develops and verifies empirically a model, where technological change is a function of intelligent adaptation, which maximizes the appropriation of energy from the environment. Empirical research presented in the article suggests that food deficit is a powerful spur of technological change, and the loop between said change and appropriation of energy works is the most visible in societies with such deficit. As the human civilisation has managed to cut the average food deficit by half, since 1992, whist doubling population, we might be, right now, at the historical peak of intensity in technological change.

1 Introduction

The economic theory of innovation and technological change is based on the assumption that said technological change means improvement. The link between technological change and economically measurable progress is almost axiomatic. Almost, because empirical data partly contradicts that assumption. This article presents an alternative, theoretical model, together with its empirical verification, where technological change is represented as a process of collective experimentation, based on an evolutionary function of intelligent adaptation.

In 2016, the World Bank, in the series entitled 'World Economic Prospects', published a report entitled 'Digital Dividends' (World Bank 2016[1]), where a very clear statement has been made: the entire human civilisation is far from exploiting all the potential gains we could possibly have out of digital technologies, in their current state of development. The assumption underlying this statement is that technological change should produce unequivocal, social and economic progress. The assumption of technological change producing economic improvement probably goes back to Joseph Schumpeter and his theory of business cycles (see Schumpeter 1939[2]). Schumpeter assumed that some scientific inventions convey a special kind of economic change, able to push the economy off the neighbourhood of general Walrasian equilibrium, and, on the long run, to improve the efficiency of the production functions prevailing in business.

The concept of efficiency in production, called productivity, is older than the Schumpeterian theory. Yet, the classics of economics, like Adam Smith and David Ricardo, stated generally that productivity is the key to successful business practice, and that business actions taken by business people simply display different levels of efficiency. Social thinkers with a moral edge, like John Stuart Mill, would argue that it is a good thing to develop efficient practices, and generally a bad habit to indulge in inefficient ones. This, in turn, implied some kind of diversity in productivity existing in the social fabric around us. Still, the systematic association between technological change and incremental improvement in productivity seems to be the invention of Joseph Schumpeter, who used to perceive technologies as something akin to hurricanes. His question was simple: when two or more hurricanes meet at some point, which one prevails? Answer: the most powerful one. The transformative power of new technologies was supposed to be observable as their capacity to increase efficiency in the use of production factors, or their productivity.

The Schumpeterian paradigm found a formal confirmation in the neoclassical stream of economic sciences. The theory of Edmund Phelps and his notion of 'golden rule' regarding investment and innovation (see for example Phelps 1964[3]). However, the picture of technological progress has been becoming more and more blurred over the last five decades. Research presented by Kenneth Arrow clearly suggested that actual technological change is far from being optimal regarding the needs of the society (Arrow 1962[4], 1969[5]). On the other hand,

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[1] International Bank for Reconstruction and Development (The World Bank), 2016, The World Development Report: Digital Dividends, ISSN: 0163-5085; ISBN: 978-1-4648-0671-1; e-ISBN: 978-1-4648-0672-8; DOI: 10.1596/978-1-4648-0671-1

[2] Schumpeter, J.A. (1939). *Business Cycles. A Theoretical, Historical and Statistical Analysis of the Capitalist Process.* McGraw-Hill Book Company

[3] Phelps E.S., 1964, Models of Technical Progress and The Golden Rule Of Research, Cowles Foundation Discussion Paper no. 176, October, 16

[4] Arrow K.J., 1962, Economic Welfare and The Allocation of Resources for Invention, in: Nelson R. (ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors, NBER Princeton University Press 1962

[5] Arrow, K.J., 1969, The Firm in General Equilibrium Theory, Technical Report no. 3, Prepared Under Contract No. N00014-67A-0298-0019, Project no. NR 047-004, Harvard University, May 1969

quite a foundational research by Frederic Scherer provided convincing evidence that innovation as an actual business practice was much more about hierarchy in technological race than about optimizing productivity (Scherer 1967 [6]). The structuring and hierarchizing function of technological change was strongly emphasized by Loury (1979[7]) and well as by Kamien and Schwartz (1982[8]).

The Schumpeterian process of technological progress can be decomposed into three parts: the exogenous scientific input of invention, the resulting replacement of established technologies, and the ultimate growth in productivity. Empirical data provides a puzzling image of those three sub-processes in the modern economy. Data published by the World Bank regarding science, research and development allow noticing, for example, a consistently growing number of patent applications per one million people in the global economy (see http://data.worldbank.org/indicator/IP.PAT.RESD). On the other hand, Penn Tables 9.0 (Feenstra et al. 2015[9]) make it possible to compute a steadily growing amount of aggregate amortization per capita, just as a growing share of aggregate amortization in the global GDP. Still, the same Penn Tables 9.0, indicate unequivocally that the mean value of Total Factor Productivity across the global economy has been consistently decreasing since 1979 until 2014. This presently observable trend is essentially a confirmation of what used to be a concern already twenty years ago (see for example: Frantzen 2000[10])

Of course, there are alternative views of measuring efficiency in economic activity. It is possible, for example, to consider energy efficiency as informative about technological progress, and the World Bank publishes the relevant statistics, such as energy use per capita, in kilograms of oil equivalent (see http://data.worldbank.org/indicator/EG.USE.PCAP.KG.OE). Here too, the last decades do not seem to have brought any significant slowdown in the growth of energy consumption. The overall energy-efficiency of the global economy, measured with this metric, is decreasing, and there is no technological progress to observe at this level. A still different approach is possible, namely that of measuring technological progress at the very basic level of economic activity, in farming and food supply. The statistics reported by the World Bank as, respectively, the cereal yield per hectare (see http://data.worldbank.org/indicator/AG.YLD.CREL.KG), and the depth of food deficit per capita (see http://data.worldbank.org/indicator/SN.ITK.DFCT), allow noticing a progressive improvement, at the scale of global economy, in those most fundamental metrics of technological performance.

Thus, the very clearly growing effort in research and development, paired with a seemingly accelerating pace of moral ageing in established technologies, occurs together with a decreasing Total Factor Productivity, decreasing energy efficiency, and just very slowly increasing efficiency in farming and food supply chains. What exactly is happening? Are we, as a civilization, utterly inefficient in our technological change? Or, maybe, the Schumpeterian expectations of ever-growing productivity were simply overshot and this is time to revise them?

There is a strong temptation to qualify this state of things as dysfunctional regarding the purposes of technological change. The World Development Report 2016 by the World Bank, mentioned earlier in the introduction, seems to share this view, at list partly. Whilst putting

[6] Scherer, F.M., 1967, Research and Development under Rivalry, Quarterly Journal of Economics, no. 71, pp. 359 – 394
[7] Loury G.C., 1979, Market structure and innovation, Quarterly Journal of Economics, 1979, no. 93, pp. 395 – 410
[8] Kamien M.I. , Schwartz N.L., 1982, Market Structure and Innovation, Cambridge Universitry Press, Cambridge 1982
[9] 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
[10] Frantzen D., 2000, Innovation, technological diffusion and the influence of R&D, Cambridge Journal of Economics, vol. 24, pp. 193 – 210

forth the possible gains from digital technologies, the authors suggest some kind of dysfunction on the path of progress. A significant stream of research claims that real technological progress requires more spill-over of inventions from the rich, developed economies towards and into the developing ones. Intellectual property is frequently pointed at as the prime culprit of insufficient diffusion. A whole plethora of scholars seems sharing this view (see for example: Jaffe et al. 1982[11]; Eaton, Kortum 1999[12]; Kauffman Foundation of Entrepreneurship 2011[13]).

Still, we might be facing a misunderstanding in expectations rather than a dysfunction in action. The very concept of Total Factor Productivity is based on the theory of production function, based on the seminal research presented by Prof Charles W. Cobb and Prof Paul H. Douglas, in their common work from 1928[14]. The declared intention of their research was to find a way of distilling progress as distinct from simple accumulation. The intriguing conclusion of their paper says: '*Thus we may hope for: (1) An improved index of labour supply which will approximate more closely the relative actual number of hours worked not only by manual workers but also by clerical workers as well; (2) a better index of capital growth; (3) an improved index of production which will be based upon the admirable work of Dr. Thomas; (4) a more accurate index of the relative exchange value of a unit of manufactured goods. In analysing this data, we should (1) be prepared to devise formulas which will not necessarily be based upon constant relative "contributions" of each factor to the total product but which will allow for variations from year to year, and (2) will eliminate so far as possible the time element from the process*'. The last sentence is probably the most intriguing. Today, we use the Cobb-Douglas production function for assessing exactly the class of phenomena those two scientists had the most doubts about: changes over time. They clearly suggest that the greatest weakness of their approach is robustness over time, and this is exactly what we do with their model today: we use it to assess temporal sequences. On the other hand, as one studies the methodology of the model presented by Cobb and Douglas, the parameters of their equation are presented as essentially stable in time. It is worth noticing that absolutely nothing in that seminal method suggests that coefficients of productivity should grow with time.

The present article presents a different approach to technological change, based on the previously cited empirical observation that technological changes in the global economy are associated with significant improvement in food supply: since 1992 through 2016, the global average food deficit has been cut by half whilst the human population doubled. This is a huge achievement, even in the presence of decreasing Total Factor Productivity. The theoretical challenge consists in explaining this phenomenon so as to create a tool of prediction for the future. The fundamental theoretical hurdle to jump over seems to be the distinction between function and purpose. Charles W. Cobb and Paul H. Douglas demonstrated convincingly that output can grow beyond what could result from simple accumulation of production factors, and later, this surplus of growth has been labelled 'Total Factor Productivity'. Still, there is no convincing evidence that technological change seen from the behavioural perspective is an activity oriented on creating that outcome. It seems sensible to go back to the Nobel-prized fundamentals of behavioural economics, thus to the seminal work of John Nash (see for

[11] Jaffe A. , Bound J. , Cummins C. , Griliches Z. , Hall B.H., 1982, Who Does R&D and Who Patents ?, National Bureau of Economic Research Working Papers, Working Paper No. 908, Cambridge MA 1982
[12] Eaton J., Kortum S., 1999, International Technology Diffusion: Theory and Measurement, International Economic Review, Boston, August 1999, pp. 537 – 565
[13] Ewing Marion Kauffman Foundation, 2011, Rules For Growth. Promoting Innovation and Growth Through Legal Reform, ISBN 978-0-9831775-0-0
[14] Charles W. Cobb, Paul H. Douglas, 1928, A Theory of Production, The American Economic Review, Volume 18, Issue 1, Supplement, Papers and Proceedings of the Fortieth Annual Meeting of the American Economic Association (March 1928), pp. 139 - 165

example: Nash 1951[15]), and something that seemed a polemic discussion from the part of Herbert W. Simon (Simon 1955[16]). That early, fundamental research showed that there is nothing essentially long-sighted in the way we do business and make our economic choices. The concept of 'dominant strategy', coined up by John Nash, still remains very largely a puzzle: there is typically a discrepancy between what we think is the path to highest payoff, and what this path really is, and yet we cannot really estimate that discrepancy. If we could, there would be no discrepancy. The theory of games with imperfect recall by Reinhard Selten (see for example: Selten 1975[17]) suggests quite convincingly that whatever rationality we build up for predicting the outcomes of our actions, this rationality will anyway be forgotten as our achievements will become history, in the presence of limited cultural memory. Research by Nelson and Pack, among others, show that economic optimization is simply not what is being done in real business (Nelson, Pack 1997[18]).

Much more recent developments in the lines of evolutionary theory, such as the Adaptive Markets Hypothesis by Andrew W. Lo (Lo 2005[19]), suggest a plausible representation of economic decisions as imperfectly rational, yet intelligent adaptation to opportunities offered by the environment. The present article develops in this line of evolutionary thinking: economic decisions can be represented as a sequence of experiments oriented on immediate, short-term results, where these short-term goals might be irrational from the perennial perspective, and yet the process of experimenting, in itself, is a case of intelligent adaptation.

Given the stylized facts at hand and the above-stated theoretical fundamentals, a **general hypothesis** is being stated, and developed, in the next section, in the form of a model: **technological change in the economy has the biological function of maximizing the human appropriation of energy from the environment.**

2   The model

The model presented below is partly inductive and empirical, and partly speculative. Some of its propositions are verifiable, and are being verified empirically in the following section, whilst the most general theoretical framework is speculative to the extent that no direct evidence can be presented to check it. Thus, it is postulated that the interaction of human population with its environment manifests itself, among other phenomena, in a certain appropriation of energy[20]. We can empirically measure this appropriation as final energy use, and as the consumption of food. Most probably some residual appropriation of energy occurs, and still remains unmeasured. The process of appropriating energy from the environment is imperfectly efficient in a probabilistic way: sometimes more energy is appropriated than spent by a human community (success), sometimes more energy is spent (failure).

[15] Nash, J., 1951, Non-Cooperative Games, The Annals of Mathematics, Second Series, Volume 54, Issue 2 (September, 1951), pp. 286 - 295
[16] Simon A.,H., A Behavioral Model of Rational Choice, The Quarterly Journal of Economics, Vol. 69, No. 1 (Feb., 1955), pp. 99-118
[17] Selten, Reinhard. "Reexamination of the perfectness concept for equilibrium points in extensive games." International journal of game theory 4.1 (1975): 25-55.
[18] Nelson, R. R., Pack, H., 1997, The Asian Miracle and Modern Growth Theory, The World Bank, October 1997
[19] Lo, A.,W., 2005, Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis, The Journal of Investment Consulting, Volume 7, no. 2, pp. 1 - 24
[20] Should anyone refer the notion of 'appropriation' to the legal context, the model treats appropriation as natural possession, and not as property rights.

Basing on the brilliant, posthumously published insights by reverend Thomas Bayes, it is further assumed that in the presence of uncertain outcomes in an action, and of an impossibility to measure directly the odds of satisfactory outcomes, we have all the interest in multiplying alternative combinations of successes and failures (see Bayes, Price 1763[21] p. 384). Each piece of what we call 'material civilization', i.e. each social structure, technology, institution etc. can be seen as another combination of successes and failures in appropriating energy from environment. At a given moment t, any human community has at their disposal a set TC(t) = $\{tc_1, tc_2, ..., tc_n\}$ of n technologies, which allows the appropriation of a certain amount of energy, observable as final energy use and food consumption.

Technological change consists in replacing an older set of technologies with a newer one. The process of invention is being accompanied by a process of obsolescence. At this point, a relatively strong and tentative assumption is being made, almost as a speculative hypothesis, namely that the observable manifestations of thus defined technological change – patent applications, R&D expenditures, amortization of established technologies etc. – are manifesting a broader and deeper, overarching process of continuous social experimentation, in which we multiply the possible combinations of successes and failures in appropriating energy from the environment. This process both allows the emergence of and engages productive resources: labour and capital. Following the intuition expressed by Cobb and Douglas (Cobb, Douglas 1928 op.cit., p. 139), the process of accumulation in productive resources is seen as at least partly distinct from the invention of new technologies.

Before further theoretical development, two stylized facts are worth exposing. Firstly, two, mutually contradictory trends of change are observable as for the final energy use. At the microeconomic level, the current trend in engineering is to minimize energy consumption per unit of output in every individual technology adopted. Yet, we stack up a growing number of thus optimized technologies, and, at the macroeconomic level, the average energy use per capita in the global economy keeps growing. Secondly, as a civilisation, we are still slightly starving. Whilst the food deficit has been cut by half since the early 1990ies, it is still present, i.e. the average human being on this planet still lacks over 80 kilocalories per day. Thus, the appropriation of energy through eating, for our civilisation as a whole, is still an attempt to reach repletion.

Given both the theoretical considerations, and the stylized facts mentioned, the following general structure is being stated, as in equation (1), where 'EG' represents final energy use per capita, 'FD' is food deficit per capita, 'R' represents the amount of productive resources, and ΔTC represents the pace of technological change, i.e. the compound pace of both invention and obsolescence in established technologies.

$$\begin{Bmatrix} EG \\ FD \end{Bmatrix} = f \begin{Bmatrix} R \\ \Delta TC \end{Bmatrix} \qquad (1)$$

It is worth noticing that the general structure expressed in equation (1) de facto implies a loop of retroaction. It can be assumed, as well, that the right side of (1) is a function of the left side, i.e. the set of technologies evolves through intelligent adaptation, i.e. societies undertake continuous attempts to maximize their hold of energy from environment through innovation.

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[21] Mr. Bayes, and Mr Price. "An essay towards solving a problem in the doctrine of chances. by the late rev. mr. bayes, frs communicated by mr. price, in a letter to john canton, amfrs." Philosophical Transactions (1683-1775) (1763): 370-418; Stable URL: http://www.jstor.org/stable/105741; last accessed on Mon, 28 Aug 2017 05:09:04 UTC

In order to clear the path towards empirical check, both the structure (1), and its retroactive loop, can be straightforwardly transformed into a set of logarithmic equations, suitable for linear regression. With 'S' standing for the scale factors, and 'b' representing the residual component, equations (2) - (5) represent such a transformation.

$$ln(EG) = a_1 * ln(S) + a_2 * ln(R) + a_3 * ln(\Delta TC) + b_1 \qquad (2)$$

$$ln(FD) = a_4 * ln(S) + a_5 * ln(R) + a_6 * ln(\Delta TC) + b_2 \qquad (3)$$

$$ln(R) = a_7 * ln(S) + a_8 * ln(EG) + a_9 * ln(FD) + b_3 \qquad (4)$$

$$ln(\Delta TC) = a_{10} * ln(S) + a_{11} * ln(EG) + a_{12} * ln(FD) + b_4 \qquad (5)$$

3 The empirical check

3.1 The dataset and the methodology

In order to verify the model presented in the preceding section, a compound database has been used. The core of the dataset is made of Penn Tables 9.0 (Feenstra et al. 2015[22]), and this core has been updated by the author with the previously mentioned (see 'Introduction') data from the World Bank regarding food deficit, energy consumption, as well as regarding patent applications. Energy use per capita (in kg of oil equivalent a year), as well as food deficit (in kilocalories per day per person), have both been taken as such from the resources of the World Bank. The author computed his own two indicators in order to estimate the pace of technological change. The first is the number of resident patent applications per million people, later symbolized as '**Pa/Pop**'. The second indicator of ΔTC, symbolised with the acronym '**DP/Q**' is the share of GDP, output side (the 'rgdpo' variable in Penn Tables), taken by the aggregate amortization of physical capital. Hence, the factor **$ln(\Delta TC)$** is being split into those two distinct measures on the explanatory side of the corresponding equations, and, logically, equation (5) mutates into (5a) and (5b), with those two measures of innovation as respective outcome variables.

A methodological doubt arises at the crossing of scale factors in equations (2) – (5), and all the other components. It is reasonable to assume that output (**Q**) and population (**Pop**) make the two principal factors of scale, and yet they are the denominators of other variables. Co-integration is to expect, and still it is interesting to check its impact on the model. Thus, output and population has been kept as scale factors in the empirical version of equations (2) – (5), with an option to hold them constant and test the model in hypothetically stationary conditions. A similar concern is connected to the general category of production factors, or **$ln(R)$** in the equations presented above. It seemed logical to treat it analytically as something distinct from simple scale factors. Thus, the input of capital and labour has been introduced, in the empirical check, as intensities: physical capital per capita (**CK/Pop**), and the average number of hours worked per person employed (**AVH**). This, in turn, makes the equation (4) mutate into (4a) and (4b), with those two distinct metrics on the left side. On the whole, the presence of scale factors in the model, as it is being tested empirically, is considered as a case of factorization, according

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[22] 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

to the pattern: a = b*(a/b). As the variables pertaining to technological change and to the accumulation of production factors are essentially coefficients, the denominators of those coefficients are being pulled out of brackets as scale factors, in order to show their relative influence.

The depth of food deficit is actually reported as non-null only in some countries, mostly the developing ones and emerging markets. A logarithmic equation with food deficit inside will naturally render valid observations only in those cases, passing over all the developed economies, as well as over most recent periods of relative opulence in some emerging markets. On the other hand, most of the recorded amortization in physical capital, as well as most of resident patent applications are to be found in those non-starving populations. Thus, it is to keep in mind that equation (3) is being tested only as for countries with explicit food deficit. For the same reasons, in equations (4) and (5), food deficit has been used as control variable. Each equation is being tested with food deficit explicitly added as explanatory variable – thus limiting the empirical check to countries with actual non-null food deficit – as well as without that variable, in the whole sample of observations, valid regarding other variables. In other words, equations (4) and (5) are being used to generate an explanation what happens in the model, when the population in question officially starves. In analytical terms, equations (4a), (4b), (5a), and (5b) further split into versions corresponding to the presence or absence of food deficit in the model.

As the model under verification is strongly oriented on what social structures actually do, the residual component 'b' has been theoretically decomposed before empirical check, so as to capture some structural patterns. Thus, natural logarithm of the **density of population** has been added – quite intuitively - to each equation, as structural parameter. Additionally, after each test, the empirically obtained residual has been tested for the correlation of its distribution with other variables in the database used.

3.2 Results of linear regression

Tests have been conducted with the OLS method, using Wizard for MacOS software. **Equation (2)** has been tested as the first. In the basic version, i.e. with scale factors, it yielded **n = 1862** valid observations, and a coefficient of determination equal to $\mathbf{R^2 = 0,863}$. Coefficients of regression are specified in Table 1, below. The ΔTC component, such as it is being compounded of two distinct variables, seems to have the contrary impact, on energy use, to that of the input of production factors. The faster the technological change happens, the greater is the use of energy per capita. On the other hand, greater intensity in the input of production factors acts the opposite way. The density of population, whilst significant in its correlation with the outcome variable, does not show much impact on it. Scale factors – output and population – very largely cancel each other. The residual constant did not yield significant correlation with any other variable in the sample. After the removal of scale factors, the coefficient of determination fell just slightly, down to $\mathbf{R^2 = 0.838}$, but the coefficients, specified in Table 2 further below, changed noticeably. Whilst remaining all robust, some of them changed their signs. Two provisional conclusions can be drawn: the scale factors are, indeed, co-integrated with other explanatory variables, and yet their presence in the empirical check does not change significantly the overall explanatory power of the equation tested. The residual constant, once again, yielded no significant correlation with other variables in the database.

Table 1 Empirical check of equation (2), basic version with scale factors

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	0,885	0,062	14,239	0,000
ln(Pop)	-0,857	0,063	-13,708	0,000
ln(Avh)	-0,267	0,063	-4,237	0,000
ln(ck / pop)	-0,276	0,051	-5,43	0,000
ln(DP/Q)	0,318	0,056	5,729	0,000
ln(Density of population (people per sq km))	-0,082	0,006	-13,152	0,000
ln(Pa / pop)	0,147	0,007	22,226	0,000
constant	4,484	0,562	7,976	0,000

Source: author's

Table 2 Empirical check of equation (2), stationary version without scale factors

variable	coefficient	std. error	t-statistic	p-value
ln(Avh)	-0,314	0,074	-4,222	0,000
ln(ck / pop)	0,441	0,014	31,874	0,000
ln(DP/Q)	-0,24	0,041	-5,852	0,000
ln(Density of population)	-0,07	0,007	-10,71	0,000
ln(Pa / pop)	0,18	0,006	30,629	0,000
constant	4,457	0,665	6,697	0,000

Source: author's

Passing to equation (3), we narrow down the scope of empirical check to developing countries and emerging markets with officially recorded food deficit. The sample of valid observations is noticeably smaller, with **n = 328**, and yet the overall explanatory power of the equation, in the basic version with scale factors, remains high, at $\mathbf{R^2 = 0,767}$. Table 3, below, gives the coefficients of regression for this specific test. One thing is to keep in mind: the food deficit, as it is being reported by the World Bank, is a deficit in real terms, but a positive value in the corresponding dataset. Thus, a negative coefficient of regression means that the given variable contributes to decreasing food deficit, thus to increasing appropriation of energy. With that reserve kept in mind, the coefficients of equation (3) are remarkably coherent with those obtained in the empirical check of equation (2). The intensity of technological change is definitely associated with lower a food deficit, with the pace of obsolescence in established technologies, measured as share of aggregate amortization in the GDP, capturing most of this particular correlation. Differently from equation (2), the residual of equation (3) finds a significant correlation outside the model, namely with the so-called welfare-relevant TFP at constant national prices (2011=1), with Pearson correlation at r = 0,381.

As the stationary version of equation (3) is tested, without scale factors (see Table 4, further below), a case similar to equation (2), although not identical, can be observed. Once the scale factors are removed from the model, coefficients of the remaining variables change, including their signs. The predominantly important intensity of amortization, as share in the GDP, acquires a positive sign, and seems contributing to increase the food deficit. The overall explanatory power of the equation devoid of scale factors fall down to $\mathbf{R^2 = 0,608}$. Interestingly, the residual constant of the equation becomes largely random, with a p – value of 0,478, and it becomes significantly correlated with many other variables in the database: a) TFP level at current PPPs (r = - 0,587) b) Welfare-relevant TFP at current PPPs (r = - 0,563) and c) rate of

amortization in fixed assets (r = - 0,379)[23]. Certainly, equation (3) is very sensitive to the presence of the two scale factors: aggregate output and population. In particular, and this is common with equation (2), the factor of aggregate amortization as share of the GDP, is very sensitive to the presence or absence of these metrics. Going a little in advance of results pertaining to equations (4) and (5), presented further below, testing their stationary forms (no scale factors) brings results broadly similar to equation (2) rather than equation (3). For that reason, and as equations (4) and (5) mutate into four varieties each, according to the empirical variables chosen for the left side, and to the inclusion of food deficit, in the tests that follow scale factors are kept in the model.

Table 3 Empirical check of equation (3), basic version with scale factors

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	-4,213	0,367	-11,485	0,000
ln(Pop)	4,072	0,368	11,072	0,000
ln(DP/Q)	-1,1	0,25	-4,409	0,000
ln(Pa/Pop)	-0,131	0,031	-4,287	0,000
ln(Density of population)	-0,098	0,051	-1,92	0,056
ln(ck / pop)	2,727	0,309	8,826	0,000
ln(avh)	4,279	0,513	8,34	0,000
constant	-19,006	4,	-4,751	0,000

Source: author's

Table 4 Empirical check of equation (3), stationary version, without scale factors

variable	coefficient	std. error	t-statistic	p-value
ln(DP/Q)	1,46	0,2	7,291	0,000
ln(Pa/Pop)	-0,226	0,029	-7,775	0,000
ln(Density of population)	-0,146	0,062	-2,341	0,020
ln(ck / pop)	-0,83	0,087	-9,545	0,000
ln(avh)	2,52	0,604	4,176	0,000
constant	-2,951	4,152	-0,711	0,478

Source: author's

The results of empirical check regarding equations (2) and (3) allows a cautious, tentative conclusion that in the presence of scale factors, innovation is positively correlated with higher an appropriation of energy from environment, whilst basic accumulation of production factors acts in the opposite way and is associated with lower an appropriation of energy. In the absence of scale factors, the impact of innovation becomes ambiguous. The pace of technological change measured at the level of amortization seems, then, to have a negative impact on the appropriation of energy, whilst the impact of invention (patent applications per million people) remains positive, though weak. Scale factors, as explanatory variables, seem to cancel each other. They are output and population, and their opposite signs suggest that their mutual ratio, namely GDP per capita, is the key answer to that ambiguity. Keeping in mind the inverted reading of food deficit (positive number measuring something negative), a coherent path emerges: the greater the wealth measured with GDP per capita, the greater the appropriation of energy per capita.

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[23] This variable is distinct from the share of amortization in the GDP, used in the model. In this case, this is the simple, basic rate of amortization, averaged for the given country – year, as reported in Penn Tables 9.0.

The next step consists in testing the many mutations of equations (4) and (5) in the model. These equations focus on the strictly spoken intelligent adaptation, and their empirical testing attempts at finding patterns in how societies react to the fact that innovation brings them more energy from environment. The testing starts with **equation (4aa)**, where the input of production factors (left side of the equation) is represented with the **ratio of physical capital per capita (CK/Pop)**, and food deficit is provisionally left outside the model. This is the general case of (4a). With **n = 2 348** valid observations, this equation yields a surprisingly high explanatory power, at **$R^2 = 0,975$**, and yet, the loop of intelligent adaptation, assumed in the theoretical model, is surprisingly weak. Studying the coefficients, provided in Table 5, below, one can see that energy use per capita, supposed to represent energy appropriation in this version of the equation, has negligible an impact on the accumulation of physical capital. The fact of consuming more or less energy does not seem to have much influence on how intensely physical capital is being accumulated. The residuals of (4aa) are interestingly correlated with the supply of money measured as a share of capital stock (Pearson correlation r = - 0,332).

Table 6, further below, shows the coefficients of equation (4ab), thus we are still explaining the **ratio of physical capital per capita (CK/Pop)** on the left side, and this time food deficit is incorporated into the explanation, narrowing down the sample of observations to developing countries and some emerging markets. The so-truncated sample yields **n = 533** country-year observations, with a coefficient of determination equal to **$R^2 = 0,957$**. The coefficient attributed to food deficit is similar to that of energy use per capita, and they are both generally coherent with the results obtained as for equation (4aa). In other words, this particular loop of intelligent adaptation seems working quite feebly. An interesting path of further possible exploration opens up as one studies the correlations of residuals. Residuals from equation (4ab) are significantly correlated with many other variables in the database: average hours worked per person (r = - 0,438), human capital index (r = 0,429), TFP level at current PPPs (r = - 0,453), welfare-relevant TFP levels at current PPPs (r = - 0,461), share of labour compensation in GDP at current national prices (r = 0,332), amortization rate (r = - 0,863), and supply of broad money as share of capital stock (r = - 0,525). Of course, the detailed investigation of all those correlations would take another scientific paper to write, and still, for now, it can be cautiously stated that this particular loop of intelligent adaptation is more complex than the basic theoretical model suggests.

Table 5 Empirical check of equation (4), version (4aa), CK/Pop on the left side, food deficit outside the model

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	1,053	0,012	88,705	0,000
ln(Pop)	-1,052	0,012	-90,681	0,000
ln(DP/Q)	0,968	0,016	62,158	0,000
ln(Pa/pop)	-0,018	0,004	-4,908	0,000
ln(Energy use (kg of oil equivalent per capita))	0,018	0,012	1,45	0,147
ln(Density of population)	-0,015	0,003	-5,899	0,000
Constant	2,507	0,101	24,862	0,000

Source: author's

Table 6 Empirical check of equation (4), version (4aa), CK/Pop on the left side, food deficit in the model

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	0,98	0,027	36,098	0,000
ln(Pop)	-0,987	0,027	-37,21	0,000
ln(DP/Q)	0,818	0,026	30,895	0,000
ln(Pa/pop)	-0,004	0,005	-0,855	0,393
ln(Energy use (kg of oil equivalent per capita))	0,088	0,02	4,324	0,000
ln(Depth of the food deficit (kilocalories per person per day))	0,043	0,009	4,675	0,000
ln(Density of population)	-0,062	0,008	-8,021	0,000
constant	2,348	0,259	9,068	0,000

Source: author's

Now, equation (4) is being tested with a different variable on the left side, to be explained, namely **the coefficient of hours worked per person employed (AVH)**. Once again, we start with the general sample of countries, and so with food deficit provisionally left outside the model. This is being labelled as equation **(4ba)**, and it yields **n = 1 939** valid observations in the database, which explain less than 40% of variance on the left side: $\mathbf{R^2 = 0,378}$. This version of equation (4) is probably the most puzzling empirical test among all those presented in this article. The relatively low coefficient of determination is associated with a residual, which does not display any significant correlation with other variables in the database. Either the general logic of equation (4) simply does not work in the case of this empirical variable on the left side (average supply of labour per person), or we are measuring something really autonomous, which would require a different model to be fully explained. Interestingly, the situation changes completely when equation (4) gets mutated into **(4bb)**, this still explaining the supply of labour, but this time with food deficit among the explanatory variables. Although the sample of observations gets shaved off dramatically, down to **n = 317**, the overall explanatory power rises up to $\mathbf{R^2 = 0,632}$. The coefficients of regression, presented in Table 8, further below, suggest that this time, the loop of intelligent adaptation does work in the lines of the theoretical model. Energy use per capita, in particular, appears as a definite kick-off for the supply of labour. Thus, in a society constrained with various degrees of starvation, innovation can spur intelligent adaptation, which, in turn, makes people work more. The residual of equation (4bb) is puzzlingly correlated with local exchange rates (r = - 0,309).

Table 7 Empirical check of equation (4), version (4ba), AVH on the left side, food deficit outside the model

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	-0,102	0,007	-13,744	0,000
ln(Pop)	0,105	0,007	14,747	0,000
ln(DP/Q)	0,015	0,01	1,564	0,118
ln(Pa/pop)	0,013	0,002	5,26	0,000
ln(Energy use (kg of oil equivalent per capita))	-0,025	0,007	-3,351	0,001
ln(Density of population)	0,006	0,003	2,237	0,025
Constant	8,666	0,067	128,847	0,000

Source: author's

Table 8 Empirical check of equation (4), version (4bb), AVH on the left side, food deficit in the model

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	-0,074	0,013	-5,648	0,000
ln(Pop)	0,058	0,011	5,149	0,000
ln(DP/Q)	-0,013	0,017	-0,786	0,432
ln(Pa/pop)	-0,016	0,004	-4,071	0,000
ln(Energy use (kg of oil equivalent per capita))	0,186	0,011	16,728	0,000
ln(Depth of the food deficit (kilocalories per person per day))	0,034	0,003	10,762	0,000
ln(Density of population)	0,059	0,004	14,05	0,000
constant	6,683	0,147	45,52	0,000

Source: author's

The last step of empirical investigation consists in checking **equation (5)**. In a fashion similar to equation (4), four different mutations of (5) are being verified, starting with the one labelled **(5aa)**, where **the pace of technological change is represented with aggregate amortization as a share of GDP**, and food deficit is left outside the model so as to encompass a general case. Said general case covers **n = 2 594** valid observations, yielding a coefficient of determination equal to $R^2 = 0,804$. The coefficients of (5aa), presented in table 9, below, suggest rather the classical logic of accumulation than the loop of intelligent adaptation postulated in the model: intensity in the supply of production factors spurs the obsolescence of established technologies much more powerfully than appropriation of energy. On the other hand, the residual component of (5aa) seems to be truly a residual, with no significant correlation to any variable outside the model. The **(5ab) version of equation (5)** presents strikingly similar a picture (see table 10 further below). Keeping the relative burden of aggregate depreciation in the GDP as the metric of pace in technological change, but including food deficit in the game, we downscale the sample to **n = 520** valid observations, and still it does not change much to the coefficient of determination, which is equal to $R^2 = 0,796$ in this special case. The coefficients of regression stick to the same logic as in the version (5aa), very little intelligent adaptation according to the model, more of the classical production function. One detail differs: the residuals of equation (5ab) are significantly correlated with monetary variables in the database, such as the supply of money relative do GDP (r = 0,389), or the local exchange rate (r = - 0,383).

Table 9 Empirical check of equation (5), version (5aa), the pace of technological change represented with aggregate amortization as a share of GDP, food deficit left outside the model

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	-0,766	0,017	-44,423	0,000
ln(Pop)	0,773	0,017	44,364	0,000
ln(Avh)	0,224	0,031	7,262	0,000
ln(ck/pop)	0,806	0,014	58,401	0,000
ln(Energy use (kg of oil equivalent per capita))	0,05	0,008	6,66	0,000
ln(Density of population (people per sq km))	0,023	0,002	12,222	0,000
constant	-5,488	0,258	-21,235	0,000

Source: author's

Table 10 Empirical check of equation (5), version (5ab), the pace of technological change represented with aggregate amortization as a share of GDP, food deficit in the model

variable	coefficient	std. error	t-statistic	p-value
ln(Q)	-0,864	0,045	-19,133	0,000
ln(Pop)	0,887	0,045	19,656	0,000
ln(Avh)	0,771	0,08	9,587	0,000
ln(ck/pop)	0,979	0,04	24,478	0,000
ln(Energy use (kg of oil equivalent per capita))	-0,041	0,017	-2,421	0,016
ln(Density of population (people per sq km))	0,031	0,007	4,6	0,000
ln(Depth of the food deficit (kilocalories per person per day))	-0,031	0,01	-3,012	0,003
constant	-9,801	0,584	-16,781	0,000

Source: author's

As the **pace of technological change** is being estimated with a different variable, namely the **ratio of resident patent applications per one million inhabitants**, the last two empirical tests of equation (5) are being introduced. Version **(5ba)** is the general case, with food deficit left outside the model, and **n = 1 862** valid observations. The coefficient of determination remains high, at $R^2 = 0,717$, and quite robust correlations at the level of individual explanatory variables, with the exception of capital per capita (see Table 11, below). The residuals of (5ba) are significantly correlated with the supply of money relative to capital stock (r = - 0,512), as well as with price indexes in international trade (r = - 0,329 for prices in imports, r = - 0,308 for exports). Interestingly, as the empirical check moves to the special case of **(5bb)**, i.e. to countries with 'official' food deficit, and as the sample narrows down to **n = 317** observations, the overall explanatory power hardly changes ($R^2 = 0,796$), but the accuracy of regression, at the level of individual variables, diminishes noticeably (see Table 12, further below). As a matter of fact, the impact of the key culprit in the case, namely food deficit, is largely random. Obviously, different levels of food deficit are associated with very different combinations of other variables. Still, the very high and really robust coefficient attached to final energy use per capita, in both (5ba) and (5bb), suggests that this time, the loop of intelligent adaptation really works. It might be worth mentioning, too, that the residual of (5bb) is significantly correlated with the supply of money expressed as % of the capital stock (r = - 0,551), as well as with Total Factor Productivity at constant national prices (r = - 0,344).

Table 11 Empirical check of equation (5), version (5ba), pace of technological change represented with resident patent applications per million people, food deficit outside the model

variable	coefficient	std. error	t-statistic	p-value
ln(CK/pop)	-0,111	0,087	-1,269	0,205
ln(Avh)	1,334	0,267	5,001	0,000
ln(Energy use (kg of oil equivalent per capita))	1,874	0,073	25,658	0,000
ln(Q)	0,434	0,126	3,445	0,001
ln(Pop)	-0,557	0,127	-4,395	0,000
ln(Density of population (people per sq km))	0,136	0,022	6,192	0,000
constant	-23,665	2,333	-10,143	0,000

Source: author's

Table 12 Empirical check of equation (5), version (5bb), pace of technological change represented with resident patent applications per million people, food deficit inside the model

variable	coefficient	std. error	t-statistic	p-value
ln(CK / pop)	0,731	0,32	2,285	0,023
ln(Depth of the food deficit (kilocalories per person per day)	-0,117	0,099	-1,188	0,236
ln(Avh)	-3,948	1,223	-3,227	0,001
ln(Energy use (kg of oil equivalent per capita))	2,483	0,245	10,152	0,000
ln(Q)	-0,574	0,48	-1,198	0,232
ln(Pop)	0,511	0,455	1,124	0,262
ln(Density of population (people per sq km))	0,661	0,083	8,005	0,000
constant	9,678	8,974	1,078	0,282

Source: author's

4 Conclusion

Empirical research, presented in the preceding section, proves that a standard pattern of economic growth, i.e. scale factors plus accumulation of production factors plus technological change, produces increasing appropriation of energy in the human society, both at the level of energy explicitly used in our technologies, and at the level of feeding ourselves. Hence, the basic hypothesis, stated in the introduction, has been verified empirically. The model, based on this hypothesis, assumes a loop of reaction: as technological change generates increased appropriation of energy, societies can, technically, react by adjusting said technological change to the already obtained appropriation of energy. In this respect, empirical research provides ambiguous insight: that loop of adjustment demonstrates various strength and robustness, depending on the set of variables used, and on the type of national economies we focus on. Still, a pattern emerges: when a society is really constrained in terms of energy, up to the point of starving, increased energy use seems to favour faster technological change. The 'faster' adjective has to be nuanced. Increasing final use of energy clearly favours more patentable invention, thus the kind of activity taking place at the beginning of the innovation chain, but it does not the same at the level of actual replacement in established technologies.

The interesting question at this point is 'how?'. How does the selection of technologies happen in the view of maximizing the appropriation of energy? For a moment, the reins imposed on imagination can be released and we can assume that the set of technologies established in our culture is the genetic code of said culture. When we reproduce the same set of technologies over a long time, so basically at the pace of their physical wear and tear, the genetic pattern remains the same. As we start to invent more and more different technologies, and this is precisely what we are doing now, as a civilisation, the genetic code of our culture grows more complex. Increased complexity in the genetic code requires adaptation on the part of organisms supposed to reproduce this code. We can biologically assume that reproduction of genetic code is an interaction between, on the one hand, female organisms able to recombine genes and to physically grow new organisms, and male organisms, on the other hand, specialized in standardizing and disseminating their own genome. Carrying this pattern over to social sciences, patentable invention can be paralleled to semen or seeds, and organisations supposed to absorb it and give birth to new generations of technologies are the female organisms. By the way, it turns out that the R&D sector is functionally male.

Including the pattern of sexual reproduction in this path of research opens up the interesting perspective of sexual selection, and that of the resulting hierarchizing. Female organisms and male organisms mate, and as they do so, a non-random function of preference emerges, which, in turn, creates a hierarchy of social influence in each sex. Past choices create pole positions and dead ends for future choices. Logically, the faster the pace of reproduction, the better and faster adjustment to environment we can expect: quick generational rotation creates more opportunities for bringing small corrections to the function of sexual preference and to the resulting social hierarchies. Thus, increasingly quick technological change that we can observe in the global economy could be a manifestation of intelligent adaptation without clear purpose. We are more and more on the planet (historically, we have now the biggest human population ever), the climate is changing, we are successful at shaving off the average alimentary deficit, and so we seek to adapt, by boosting the speed of social experimentation.

As we apprehend social structures under the evolutionary angle, selection and hierarchy seem to be among the key notions. Accelerating technological change, which we are witnessing right now, allows expecting increasingly sharp hierarchizing between businesses, technologies and even whole societies. Empirical research presented in this article suggest that gains from technological change, in terms of energy appropriation, produce the strongest kick-back in the presence of food deficit. Here, we reach a paradox: the lion's part of the global R&D takes place in the developed economies, where this incentive to stop starving does not exist anymore. It is possible that right now, as a civilisation, we are at the peak pace of technological change, and this pace could subside as (if at all) the global food deficit will decrease.

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