The labour-oriented, collective intelligence of ours: economic systems seen through the eyes of a neural network

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The labour-oriented, collective intelligence of ours: economic systems seen through the eyes of a neural network

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Declarations

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Not applicable: the manuscript does not report on or involve the use of any animal or human data or tissue

Consent for publication

Not applicable: the manuscript does not contain data from or regarding any individual person

Availability of supporting data

The manuscript contains hyperlinks to the datasets used in the process of research, as well as hyperlinks to Excel workbooks which contain different mutations of the perceptron used as data processing tool.

Competing interests

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Abstract

This article explores and substantiates the hypothesis that capital investment and real output in national economies are instrumental to the optimization of labour markets, i.e. human societies are oriented, most of all, on shaping their labour markets so as to assure an equilibrium between demographic growth and the set of social roles available. An original method, largely based on the Interface Theory of Perception, studies economic systems as manifestations of collective intelligence, learning by evolutionary tinkering with itself. An artificial neural network is used to study economic systems as Markov chains of states, and to discover their structuring σ -algebras, which turn out being oriented mostly on optimizing the compensation of labour and the average workload per person per year.

JEL: E01, E17, J01, J11

Keywords: collective intelligence, artificial intelligence, labour market,

Introduction

The impact of technological change on the labour market is one of the hottest topics in economics, so to say. The extent of human labour made obsolete by robotization and artificial intelligence is still to explore and discover. Even the author of this article asks himself when such pieces of scientific writing will be routinely ghost-written by artificial neural networks. The latest World Development Report (WDR) by World Bank (World Bank 2019) brings interesting observations in that respect. Apparently, at least so far, the fears of robots and digital technologies sweeping millions of jobs out of existence are unfounded. WDR 2019 brings evidence that not only don't those new technologies destroy jobs, but they also create whole new job categories and new sub-markets for human labour. Still, developing human capital is crucial: new jobs can appear, accompanying new technologies, when people acquire new skills. The most likely scenario for the global labour market is that, whilst new technologies do can create new jobs, people will have to adapt deeply in their lifestyles, including education, and cross-jobs mobility. The already proverbial 'uberization' of the labour market is a fact.

Human societies can be studied as factories of social roles. When we grow demographically, the rising headcount of humans needs to be accommodated with new slots to take in the social structure. When there are much more new humans than social slots to take, bad things, such as violent revolutions and wars tend to happen. Over millennia, we have invented social contrivances supposed to make new social roles: cities with their intense social interactions, educational systems, or, for example, the specifically European invention of quickly changing fashions in the ways we dress, which fuelled some 400 years of intense technological change through the industry of garment and textile, and thus created a stream of new occupations.

That generally anthropological assumption translates into a strong claim in the realm of economics: **capital investment and real output in national economies are instrumental to the optimization of labour markets, i.e. human societies are oriented, most of all, on shaping their labour markets so as to assure an equilibrium between demographic growth and the set of social roles available.** This is the working hypothesis of the present article, which distantly echoes the Keynesian doctrine of attaching utmost importance to proper health of the labour market. Such as it is formulated here, this hypothesis goes one step further and assumes that not only should governments take care of the labour market, but entire societies do it as a matter of fact, just with various efficacy. As one scratches its surface, controversial ramifications emerge. If desired social outcomes sum up to a balance in the labour market, the capital market could be considered as subservient and instrumental to that end. That, in turn, goes against much of the established economic (or wannabe-economic) science, which claims systemic bias of economic systems to the benefit of large capital-holders, and, correspondingly, to the detriment of the working class.

Underneath that working hypothesis as regards economics, another one dwells, more generally anthropological. The strictly economic hypothesis of general economic equilibrium is generalized into the hypothesis of collective intelligence in human societies, with general economic equilibrium being one among many manifestations thereof. Human societies are studied in this article as intelligent structures, i.e. complex wholes able to learn and evolve by experimenting with many alternative versions of themselves, whilst staying internally coherent. Each such alternative version of the coherent whole is a one-mutation neighbour to other versions, and collectively intelligent learning occurs through the

selection of the fittest mutants, regarding collectively pursued social outcomes. In other words, societies are assumed to possess the capacity for social evolutionary tinkering (Jacob 1977) through tacit coordination, such that the given society displays social change akin to an **adaptive walk in rugged landscape** (Kauffman & Levin 1987; Nahum et al. 2015).

Penn Tables 9.1 bring interesting quantitative insights to that conversation. As measured since 1950 through 2017, across 183 countries, the average number of hours worked per person per year, or ‘avh’, follows a consistently descending trend, from 2 158,41 hours in 1950, through 2 019,28 in 1980, all the way down to 1 860,90 hours in 2017 (Feenstra et al. 2015). On the other hand, the same source, i.e. Penn Tables 9.1, indicates that the relative economic effort connected to technological change has been consistently growing. With both the aggregate capital stock of fixed assets, and the GDP measured in 2011 constant national prices and expressed in millions of 2011 US\$, aggregate amortization of fixed assets takes a consistently growing average share of real output, passing from 6,5% in 1950, through 8,4% in 1980, to reach 20,5% in 2017. Interestingly, the time series of those averages, i.e. hours worked and the share of amortization in GDP, are Pearson-correlated at $r = -0,8343$. The more we need to spend, from the currently made value added, to compensate the obsolescence of our technologies, the less the average one of us works per year. The amount of human capital, conveyed by the average person employed, has been growing as the average workload in hours worked has been decreasing. The average human capital index, as given in Penn Tables 9.1, was 2,66 in 2017, against 1,82 in 1980 and 1,76 in 1950. As for the economic payoff, both capital and labour seem to be earning less and less over time. The share of labour in gross national income, measured across the 183 countries observed in Penn Tables 9.1, passed from an average of ‘labsh’ = 56,5% in 1950, to 50,7% in 2017, and the transition is quite a smooth, downwards trend. The average IRR, i.e. Internal Rate of Return on investment, has followed a similarly descending trajectory, from 19,4% in 1950 to 11,4% in 2017. Finally, against that background, one more stylized fact comes to the fore. The average national headcount of active labour force, i.e. the ‘emp’ variable in Penn Tables 9.1, grows steadily, more or less in correlation with population. Yet, when that headcount is being denominated over said population, the resulting average national coefficient of professional activity is strongly and positively Pearson-correlated with the previously mentioned share of aggregate amortization in GDP (the coefficient of correlation is $r = 0,8902$).

What if we, as a civilization, were developing digital technologies in order to accommodate a growing population with new social roles in the job market? What if the observably growing burden of aggregate amortization over the current real output of the economy was one among many manifestations of that collective struggle? For many centuries, cities served as factories of new social roles. Still, urban land needs to stay in balance with its food base, i.e. with agricultural land. Cities have limited hosting capacity. What if digital technologies were progressively taking over that traditional function of cities, by creating virtual communities, thus enhancing a new aspect of social interactions and reinforcing new skillsets, new hierarchies and new networks?

The initial hypothesis, as well as the stylized facts derived from Penn Tables 9.1 deserve projection against the background of economic literature. The coefficient of hours worked per person per year comes as truly idiosyncratic across countries, both in terms of weeks worked, and that of hours worked per week (Fuchs-Schündeln et al. 2017). In the same time, it seems being associated with the ratio of substitution between capital and labour. That ratio seems to be growing over time, and we seem to be facing a paradox: as technological change becomes faster, people work more per year. In general, between 1948 and 2009, the response of hours worked to technology shock has been varying in its shape, every 30 years, as if in a Kondratieff cycle (Cantore et al. 2017).

The coefficient of hours worked per person per year is informative both about the technologies used by people working, and about the workstyles built around those technologies. Interestingly, that coefficient seems to be inversely correlated with income, still, the correlation is rather international than intranational. When developing countries are compared with the developed ones, the average adult in the former category works about 50% more per week than the average adult in the latter group. However, inside countries, the same type of correlation reverts, and one sees richer people work more than the relatively poorer ones (Bick et al. 2018).

Somewhat in the background of research on the strictly speaking coefficient of hours worked, another question arises: do we adapt our balance between workload and leisure to our expected consumption, or maybe we do something else, i.e. form a balance between consumption and savings on the grounds of what the local labour market imposes on us? Interestingly, both approaches may be quantitatively robust (Koo et al. 2013). Research focused on the impact of institutional changes, e.g.

new environmental regulations, upon the labour market suggest that the latter is much more adaptable than in was assumed in the past, and has the capacity to offset the disappearance of jobs in some sectors by the creation of jobs in other sectors (Hafstead & Williams 2018).

Since David Ricardo, all the way through the works of Karl Marks, John Maynard Keynes, and those of Kuznets, economic sciences seem to be treating the labour market as easily transformable in response to an otherwise exogenous technological change. It is the assumption that technological change brings greater a productivity, and technology has the capacity to bend social structures. In this view, work means executing instructions coming from the management of business structures. In other words, human labour is supposed to be subservient and executive in relation to technological change. Still, the interaction between technology and society seems to be mutual, rather than unidirectional (Mumford 1964, McKenzie 1984, Kline and Pinch 1996; David 1990, Vincenti 1994). The relation between technological change and the labour market can be restated in the opposite direction. There is a body of literature, which perceives society as an organism, and social change is seen as complex metabolic adaptation of that organism. This channel of research is applied, for example, in order to apprehend energy efficiency of national economies. The so-called MuSIASEM model is an example of that approach, claiming that complex economic and technological change, including transformations in the labour market, can be seen as a collectively intelligent change towards optimal use of energy (see for example: Andreoni 2017; Velasco-Fernández et al 2018). Work can be seen as fundamental human activity, crucial for the management of energy in human societies. The amount of work we perform creates the need for a certain caloric intake, in the form of food, which, in turn, shapes the economic system around, so as to produce that food. This is a looped adaptation, as, on the long run, the system supposed to feed humans at work relies on this very work.

The method and the dataset

The here-introduced methodology attempts at testing the general hypothesis of collective intelligence, and the specific hypothesis of labour-oriented general equilibrium. The central methodological thread consists in doing something which was extremely sceptical about, i.e. in assessing what people collectively want (Bosanquet 1920). If human societies are intelligent structures, i.e. if they are able to learn by experimenting with many alternative versions of themselves and by selecting the fittest ones, the same societies need a gauging criterion to assess fitness. The here-presented method aims at finding that criterion, equating it to a collectively pursued social outcome. The intermediate goal is to reconstruct, out of quantitative macroeconomic data, the process of collective learning as regards the working hypothesis stated in the introduction. That general methodological thread is being unwrapped by using an artificial neural network as mathematical representation of an intelligent structure. This methodological path requires clearing two hurdles, namely the extent to which quantitative socio-economic data can be considered as empirical manifestation of collective intelligence, and the possibility for an artificial neural network to be a logical representation of such a collective intelligence.

When we do economics, we essentially study human behaviour. At the bottom line, economic sciences are behavioural sciences. Yet, when we have a careful look at the type of data that we work with in empirical economics, we deal with descriptive information about aggregate outcomes of human behaviour rather than manifestation of behaviour strictly speaking. The economist faces cognitive limitations akin to those of quantum physics. Individual behaviour can be observed in great detail, which, in terms of physics, is known position. Yet, the more detailed is the observation of idiosyncratic properties, the harder it is to locate those individual cases in a spectrum of probability. We can forego some of the idiosyncrasies, which we know are there, and simplify the observed cases so as to fit them in a standardized distribution of probability.

When we observe, through the lens of quantitative variables, a body of collective human behaviour, do we observe many distinct phenomena or just one structured phenomenon, which we

epistemically split into separate observables? The question digs into the foundations of empirical sciences, as outlined by William James (James 1912), and recent research in cognitive sciences further substantiates it under the heading of the Interface Theory of Perception (Hoffman et al. 2015; Fields et al. 2018). When we observe social reality, at the bottom line we might be observing primal, essentially amorph, empirical ‘stuff’, to use William James’s language, and only secondarily we partition that original empirical substance into distinct phenomena according to the practical payoff that such a partitioning can yield. At the opposite end of the theoretical spectrum, our phenomenological distinctions are assumed to be essentially true in ontological terms (Geisler, Diehl 2003; Trivers 2011; Pizlo et al. 2014).

How does phenomenological unity, or, conversely, diversity, matter for empirical economic research? When we assume that quantitative variables correspond to rigorously distinct phenomena, the baseline hypothesis is the null one, i.e. the absence of correlation. Should phenomenological unity be assumed, it is reasonable to postulate correlation, and the null hypothesis is just a methodological trick in statistics. **Thus, the hypothesis of phenomenological unity further leads to assuming the working of a collective intelligence behind many distinct, quantitative observables of social sciences.**

To what extent and how exactly does the intelligent logical structure of an artificial neural network represent collective intelligence of human societies? Artificial intelligence can be approached as the general science of intelligence, as it allows testing abstract concepts we make as regards our own mind (Sloman 1993). There are several examples in recent literature of neural networks being used as solvers in econometric models, i.e. as an alternative to stochastic regression. Accurate prediction in financial markets is a good example (Lee 2019). Even a beginner’s experience with neural networks brings that interesting, and somewhat stunning observation, that artificial neural networks have the peculiar capacity to optimize virtually everything. This strange capacity of some functions to optimize any desired outcome is so pronounced, that deep learning involves algorithms, such as the Gaussian mixture or the random forest, serving to slow down learning and prevent hasty conclusions (Zhang & Cheng 2003; Sinha et al. 2019). Apparently, even relatively simple specimens of neural networks can shed a completely new light on the ways that human societies work. In classical econometric and sociometric models, we tend to fall into the illusion of simultaneity, i.e. that everything works in the

same time and more or less at the same pace. Neural networks are based on sequence and order in experimentation and thus force the researcher to think in the same terms, i.e. in terms of a sequence of events, endowed with hysteresis (dos Santos 2017). As for strictly spoken macroeconomics, the usage of neural networks to simulate economic change can be seen as one step further beyond the application of Extended Kalman Filter (see for example: Munguia et al. 2019), i.e. as a method to include noise and error as explicit, valuable information in empirical research.

At this point, it is useful to demystify the logic of artificial neural networks. Data scientists and programmers use to say that artificial intelligence is a black box. We know it does something, we like the outcomes, yet we never quite understand how those outcomes happen, and that forced ignorance makes the engineering of AI so experimental and laborious. Yet, a few patterns are firmly drawn. An artificial neural network always performs adaptive walk in rugged landscape: it learns by producing many alternative versions of itself, which, whilst staying internally coherent, demonstrate various degrees of fitness as projected against a desired outcome. Besides defining the exact structure and sequence of equations in a piece of AI, and in the presence of any empirical dataset, the programming of neural networks passes through the fundamental distinction between input variables and the output ones. In other words, we distinguish between the valuable outcomes pursued, and the adaptive changes instrumentally serving those outcomes. That distinction can be made arbitrarily or empirically. In the latter case, before using a neural network to optimize a given variable, one can empirically select the variable which the network is the most capable to optimize with the given structure and sequence of equations. This is precisely the property of artificial neural networks which the present methodology utilizes to check the working hypothesis stated in the introduction.

The previously cited **Penn Tables 9.1** (Feenstra et al. 2015 op. cit.) **have served as the base to create an empirical dataset to be processed according to that first methodological outline.** The use of Penn Tables 9.1. is largely based on observations made as regards its earlier versions, e.g. Penn Tables 8.0: this particular database seems to be truly robust as for measuring human capital and variables pertinent to the labour market (Fang 2016). The logical structure of the neural networks used for that research is essentially that of a multi-layer perceptron (MLP), based on the propagation of local errors. Empty cells in raw data are treated, in such a logical structure, as null observations (i.e. zeros), and their

presence in the source empirical data makes the neural network rely too much on its own estimations of the outcome variable. Thus, all the incomplete ‘country-year’ observations from the original Penn Tables 9.1 dataset, i.e. observations containing empty cells, have been removed. The resulting empirical set, further called ‘**No-Empty-Cells**’ set, consists of $n = 41$ variables and $m = 3008$ ‘country-year’ observations. Meta-variables, pertaining to the quality of national statistics, have been removed. The detailed composition of this set, regarding countries and years, is provided in the Appendix, at the end of this article. Table 1, in the Appendix, gives a general view of empirical correspondence between the original set of 12 000 observations, as published in Penn Tables 9.1, and the ‘No-Empty-Cells’ set. Whilst seeming pertinent as for the core issue of this article, i.e. the labour market, the ‘No-Empty-Cells’ set is representative for relatively big economies, both GDP-wise and population-wise, with a lower than average propensity to consume, and slightly faster inflation. It is also to keep in mind that timewise, this set is slightly sloping towards relatively recent years, and, for example, does not cover the period $1950 \div 1953$, as reported in Penn Tables 9.1. For the sake of presentational convenience, the ‘No-Empty-Cells’ set of $m = 3008$ ‘country-year’ observations, will be further designated as X . In the spirit of full respect to intellectual property, the author of this article kindly asks people interested in acquiring the same empirical data to use the proprietary channel of Penn Tables, as mentioned in the above-cited reference (Feenstra et al. 2015 op.cit).

The dataset X can be considered as complex description of human activity in many distinct instances, where each ‘country $\diamond$ year’ observation is a separate phenomenal instance of a phenomenologically unique social reality. Mathematically, the entire dataset can be considered as a **Markov chain of states**, with each ‘country $\diamond$ year’ observation being a distinct state, chained to other states through a hypothetical σ -algebra. The logic of intelligent structure (i.e. different variables are manifestations of a phenomenological one) allows simulating $n = 41$ different σ -algebras, with a constant sequence of equations in the neural network, applied to optimizing, one by one, each variable among the 41 studied. Those 41 σ -algebras generate 41 different transformations S_i of X , with each σ -algebra representing, metaphorically, an adaptive walk in rugged landscape towards the top of a different hill. Each S_i can be considered as a functional aspect of the source set X , i.e. as a scenario ‘*what if humans in countries observed through the set X oriented themselves on optimizing the specific variable*

x_i as desired social outcome?'. Each S_i displays a certain degree of similarity to the source set X , and that similarity can be mathematically gauged as the Euclidean distance between the vectors of mean values in 41 variables observed in, respectively, X and S_i .

In each S_i , data is being standardized, one variable is selected as the output one, whilst the remaining 40 variables are aggregated into $\mathbf{m} = 3008$ perceptual vectors ' $\mathbf{h}$ ' as in equation (2). In the j -th perceptual vector h_j , the standardized value of the i -th input variable x_i is incremented with the error e_{j-1} , propagated from the preceding, $j-1$ -th experimental round of learning, and the incremented value is then weighed with two parameters. The $E(x_{i,j})$ parameter endogenous to the network. It is the Euclidean distance between the input variable x_i and the remaining 39 input variables in the same j -th experimental round. Its presence in equation (2) represents the internal coherence of the social system studied, as – which has already been stated before – all the variables studied are assumed to show different quantitative aspects of essentially the same set of behavioural patterns in humans. The $R \sim U([0,1])$ parameter is exogenous and quasi-random in the interval between 0 and 1. Its forces the network to experiment with different magnitudes of importance attached to input variables.

$$h_j = \sum_{i=1}^n R \sim U([0,1]) * E(x_{i,j}) * (x_{i,j} + e_{j-1}) \quad (2)$$

Error e_{j-1} is an endogenous dynamic parameter, estimated as in equation (3). The expected value of output variable $x_{o,j}$ is compared to the value yielded by the neural activation function, i.e. the hyperbolic tangent $\tanh = (e^{2h} - 1)/(e^{2h} + 1)$, through the arithmetical operation of subtraction. In each case, the observed residual difference between expected output $x_{o,j}$ and the experimental value produced through neural activation is being multiplied by (i.e. combined with) the local derivative of the corresponding activation function. The intuition behind this specific logical component is to capture both the stationary local value of a phenomenon, and its local gradient of change. Neural activation multiplied by its local derivative is essentially a constant, equal to -0,3199, modified by the presence of the perceptual vector $\mathbf{h}$. Consistently with the interface theory of perception (Hoffman et al. 2015; Fields et al. 2018), it is assumed that the network of Conscious Agents maintain a continuous state of general alertness, locally modified by perception.

$$e_j = \left[x_{o,j} - \frac{e^{2h-1}}{e^{2h+1}} \right] * \left[1 - \left(\frac{e^{2h-1}}{e^{2h+1}} \right)^2 \right] \quad (3)$$

The Euclidean distance between vectors of mean expected values in, respectively, the set X and the given set S_i , as in equation (4) below.

$$E(X; S_i) = \frac{\sum_{i=1}^n \sqrt{\left[\frac{\text{avg}(S_i; x_i) - \text{avg}(X; x_i)}{\text{avg}(X; x_i)} \right]^2}}{n} \quad (4)$$

When applied to the set X , the method described above yields a ranking of 41 transformations S_i , as regards their Euclidean similarity to X . Indirectly, that ranking of S_i translates into another ranking, namely that of variables composing the dataset X . Taking on the metaphor used earlier in this section, X represents 41 different adaptive walks which the collective intelligence of the societies studied performs in rugged landscape, each walk being oriented towards the top of a different hill. The closer the Euclidean distance between the given S_i and X , the more likely is the output variable of that S_i to be a collectively pursued social outcome.

When using artificial neural networks, in order to assess their cognitive value, it is advisable to benchmark the results they yield against something calculated in a different manner, along a different logical path. In this specific case, that gauging reference consists of multiple linear regression, computed through Ordinary Least Squares, in the same dataset X . Regression serves to test quantitative hypotheses built heuristically on the grounds of results which the artificial neural network yields, as by equations (1) – (4). The top 2, and the bottom 2 variables from the Euclidean-similarity-based ranking are taken as explained variables in multiple regression, and variables significantly Poisson-correlated with them are taken as explanatory ones. The overall explanatory power of the so-obtained multiple regressions are assessed, through the lens of their coefficients of determination R^2 , and through t -significance at the level of individual correlations.

Results and final discussion

Table 2 and Figure 1, in the Appendix, document the results of simulation run with the above-described method. Table 2 presents the Euclidean distances as computed with equation (4), between the original dataset X , and the 41 transformations S_i thereof. Figure 1 introduces an intuitive visualisation of normalized Euclidean distances $E(X;S_i)$ after inversion, thus ' $1/E(X;S_i)$ ', so as to show the hierarchy of relative importance among the $n = 41$ variables apprehended as alternative values for optimization in the experiment. Tables 3 – 6, further in the Appendix, give the results of multiple linear regression, performed on standardized values, as a cross-check for the transformations yielded by the neural networks. Canonically, variables used as explanatory in the OLS regression are those yielding robustly significant coefficients of Pearson correlation, i.e. $r \leq -0,3$ or $r \geq 0,3$.

Besides this general presentation of results, the reader can consult detailed results in two Excel workbooks, made available in the archives of the author's blog. The workbook entitled 'Comparison of Perceptrons' presents detailed calculations of Euclidean distances as in equation (4), which can be interesting to the extent that some among the 41 sets S_i display apparently absurd mean values, e.g. negative aggregate real output. The link to that file is to find in the reference list. The author attempts to give as exhaustive an interpretation of those results, yet the reader is welcome to study them directly. On the other hand, the workbook entitled 'PWT 9_1 Perceptron pegged AVH', referenced as a link in the bibliographical list further below, introduces the database used for this empirical research, as well as the logical structure of the neural network, according to equations (1) – (3), in the form of an Excel spreadsheet, in the specific version oriented on optimizing the number of hours worked (AVH) as output variable.

Probably the most striking observation about the results obtained is that only a few variables in the dataset yield meaningful results (i.e. results with non-negative mean aggregates), as collective outcomes (output variables) of the neural network formalized in equations (1) – (3). These variables are: RGDP, AVH, HC, LABSH, CSH_C, PL_X, PL_M. All the other variables, used as output ones, yield absurd results with negative mean aggregates. The collective intelligence represented in equations (1) –

(3) is able to optimize itself in elementary accord with real-life data only in those few cases. Of course, much can be studied more in depth about the logical structure of the neural network itself, still the basic observation remains: the neural network used is a standardized experimental environment and this environment yields different results according to the variable optimized as the desired outcome. Among those different results some are impossible: there is no possible social reality with negative economic aggregates. According to the methodology used the here-presented research, it is to conclude that these particular outcomes, i.e. 34 from among 41 variables tested, cannot possibly be collectively desired outcomes for the society represented in the source dataset X . This observation strongly corroborates conclusions the application of Extended Kalman Filter (Munguia et al. 2019, op. cit.), namely that macroeconomic variables vary substantially as for their predictive value. Some of them have much more meaning than others.

Interestingly, when oriented on optimizing the above-mentioned 7 variables, the neural network produces lower mean aggregates than those in the original dataset X . It is as if the collective intelligence represented by the perceptron used was steering the data towards a greater similarity with the full information available in PWT 9.1. Among the 7 variables that yield plausibly acceptable sets S_i , two clearly outrun the five remaining ones. They are: LABSH (the share of national income pertaining to the compensation of labour), and AVH (average hours worked per person per year). Should the dataset X with its 41 transformations S_i be interpreted as a **Markov chain of states**, σ -algebras oriented on optimizing these two variables have noticeably stronger a transformative power than the remaining ones. Generalizing that interpretation, the Markov chain of states represented by the set X is clearly structured: some σ -algebras are much stronger than others. If the set X and its 41 transformations S_i were an agglomeration of molecules, it would have a quasi-crystalline structure, with strongly marked cleavage planes. That, in turn, in relation to the Interface Theory of Perception (Hoffman et al. 2015 op. cit.; Fields et al. 2018 op. cit.), suggests that the logical structure studied represents the working of a network of Conscious Agents. General hypotheses of collective intelligence, and of phenomenological unity seem to be strongly substantiated. As for the strictly macroeconomic hypothesis of this article, this one also acquires strong empirical grounds with the above presented research. The latter truly indicates that **capital investment and real output in national economies are instrumental to the optimization of**

labour markets, i.e. human societies are oriented, most of all, on shaping their labour markets so as to assure an equilibrium between demographic growth and the set of social roles available.

The four multiple linear regressions, performed as cross-check for the neural network, focused on explaining top two variables from the ranking of Euclidean similarity, i.e. LABSH and AVH, together with the bottom two, which are RGDPO (Output-side real GDP at chained PPPs in mil. 2011US\$), and PL_K (Price level of the capital services, price level of USA=1). The strongest coefficient of determination, namely $R^2 = 0,999$, is achieved when explaining standardized RGDPO (with some largely aleatory correlations as per the s-significance test, though). Still, it is to remember that variables in this specific econometric model are largely cointegrated at the level of sheer size observable in national economies. In large samples, significant regression of real output on metrics such as population, labour force or the capital stock is almost tautological, and sums up to saying: yes, size matters. Regressions construed to explain LABSH and AVH yield decent levels of explanatory power, with $R^2 > 0,5$ in each case, and strong t -significances at the level of individual correlations. The fourth regression, i.e. that explaining the PL_K variable, is relatively the weakest.

As multiple regressions cross-check the results yielded by the neural network, the structuring power of LABSH and AVH, as yielded by the latter, seems to be something essentially different from the strictly speaking explanatory power of regressions built around these metrics. There is something else in the game, and that something could be collective intelligence of human societies acting as factories of social roles. The macroeconomic metrics of labour compensation LABSH and average workload AVH translate into a broader social balance between the energy required to play social roles, and the socially sanctioned rewards paid to those roles.

Should the here-presented research be taken at its face value as basis for economic policies, the Keynesian imperative of stabilizing the job market takes a different shade of tan. Apparently, labour markets optimize themselves anyway. Whatever capital resources are put at the disposition of the here-studied national labour markets, would those resources be channelled fiscally or at the monetary level, they seem being aligned on the basic imperative of balancing workload and work compensation.

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Appendix – Dataset and results

Geographical scope of the ‘No-Empty-Cells’ database selected from PWT 9.1 for being processed with the neural network (hyphenated values are the respective numbers of annual observations for each given country): Argentina – 64; Australia – 64; Austria – 64; Barbados – 11; Belgium – 64; Brazil – 64; Bulgaria – 23; Canada – 64; Chile – 63; China – 48; China, Hong Kong SAR – 54; Colombia – 64; Costa Rica – 31; Croatia – 23; Cyprus – 23; Czech Republic – 24; Denmark – 63; Ecuador – 23; Estonia – 23; Finland – 64; France – 64; Germany – 64; Greece – 63; Hungary – 38; Iceland – 54; India – 48; Indonesia – 48; Ireland – 64; Israel – 37; Italy – 64; Jamaica – 17; Japan – 64; Latvia – 23; Lithuania – 23; Luxembourg – 48; Malaysia – 48; Malta – 24; Mexico – 64; Netherlands – 64; New Zealand – 48; Nigeria – 8; Norway – 63; Peru – 64; Philippines – 48; Poland – 25; Portugal – 64; Republic of Korea – 61; Romania – 23; Russian Federation – 24; Singapore – 54; Slovakia – 24; Slovenia – 23; South Africa – 17; Spain – 64; Sri Lanka – 48; Sweden – 64; Switzerland – 64; Taiwan – 63; Thailand – 48; Trinidad and Tobago – 12; Turkey – 48; United Kingdom – 64; United States – 64; Uruguay – 28; Venezuela (Bolivarian Republic of) – 53

Temporal scope of the ‘No-Empty-Cells’ database selected from PWT 9.1 for being processed with the neural network (hyphenated values are the respective numbers of national observations for each given year): 1954 – 25; 1955 – 28; 1956 – 28; 1957 ÷ 1963 – 29 each; 1964 ÷ 1969 – 32 each; 1970 ÷ 1979 – 42 each; 1980 – 43; 1981 ÷ 1985 – 44 each; 1986 – 45; 1987 ÷ 1989 – 46 each; 1990 – 47; 1991 ÷ 1992 – 49 each; 1993 – 50; 1994 – 54; 1995 ÷ 2000 – 63 each; 2001 – 64; 2002 – 63; 2003 ÷ 2005 – 61 each; 2006 ÷ 2009 and 2013 – 60 each; 2010 ÷ 2012 and 2014 ÷ 2017 – 61 each;

Table 1 Comparison of mean values in variables studied, full Penn Tables 9.1 database vs. the ‘No-Empty-Cells’ set selected for being processed with the neural network

Acronym for the variable	Description of the variable	Mean value in the original PWT 9_1 set	Mean value in the 'No empty cells set'	Normalized Euclidean distance
rgdpe	Expenditure-side real GDP at chained PPPs (in mil. 2011US\$)	272 056,94	778 348,68	1,86
rgdpo	Output-side real GDP at chained PPPs (in mil. 2011US\$)	269 192,84	766 791,64	1,85
pop	Population (in millions)	30,74	68,16	1,22
emp	Number of persons engaged (in millions)	14,80	30,97	1,09
avh	Average annual hours worked by persons engaged	1 984,10	1 952,22	0,02
hc	Human capital index, based on years of schooling and returns to education; see Human capital in PWT9.	2,06	2,63	0,28
ccon	Real consumption of households and government, at current PPPs (in mil. 2011US\$)	198 499,76	564 898,51	1,85

cda	Real domestic absorption, (real consumption plus investment), at current PPPs (in mil. 2011US\$)	268 658,05	770 815,26	1,87
cgdpe	Expenditure-side real GDP at current PPPs (in mil. 2011US\$)	269 708,84	772 380,20	1,86
cgdpo	Output-side real GDP at current PPPs (in mil. 2011US\$)	269 769,30	769 436,58	1,85
cn	Capital stock at current PPPs (in mil. 2011US\$)	908 755,60	2 668 041,35	1,94
ck	Capital services levels at current PPPs (USA=1)	0,03	0,07	1,14
ctfp	TFP level at current PPPs (USA=1)	0,71	0,75	0,06
cwtfp	Welfare-relevant TFP levels at current PPPs (USA=1)	0,70	0,74	0,06
rgdpna	Real GDP at constant 2011 national prices (in mil. 2011US\$)	297 194,26	830 168,48	1,79
rconna	Real consumption at constant 2011 national prices (in mil. 2011US\$)	215 900,89	610 151,00	1,83
rdana	Real domestic absorption at constant 2011 national prices (in mil. 2011US\$)	289 386,29	824 465,56	1,85
rnna	Capital stock at constant 2011 national prices (in mil. 2011US\$)	1 128 532,98	3 262 012,07	1,89
rkna	Capital services at constant 2011 national prices (2011=1)	0,53	0,55	0,04
rtfpna	TFP at constant national prices (2011=1)	0,99	0,92	0,07
rwtfpna	Welfare-relevant TFP at constant national prices (2011=1)	0,97	0,93	0,04
labsh	Share of labour compensation in GDP at current national prices	0,53	0,56	0,04
irr	Real internal rate of return	0,14	0,11	0,20
delta	Average depreciation rate of the capital stock	0,04	0,04	0,09
xr	Exchange rate, national currency/USD (market+estimated)	244,63	132,26	0,46
pl_con	Price level of CCON (PPP/XR), price level of USA GDPo in 2011=1	0,38	0,51	0,36
pl_da	Price level of CDA (PPP/XR), price level of USA GDPo in 2011=1	0,38	0,50	0,33

pl_gdpo	Price level of CGDPo (PPP/XR), price level of USA GDPo in 2011=1	0,40	0,51	0,30
csch_c	Share of household consumption at current PPPs	0,64	0,59	0,08
csch_i	Share of gross capital formation at current PPPs	0,22	0,26	0,16
csch_g	Share of government consumption at current PPPs	0,19	0,17	0,15
csch_x	Share of merchandise exports at current PPPs	0,23	0,30	0,33
csch_m	Share of merchandise imports at current PPPs	(0,31)	(0,34)	0,10
csch_r	Share of residual trade and GDP statistical discrepancy at current PPPs	0,02	0,02	0,04
pl_c	Price level of household consumption, price level of USA GDPo in 2011=1	0,39	0,51	0,30
pl_i	Price level of capital formation, price level of USA GDPo in 2011=1	0,49	0,49	0,01
pl_g	Price level of government consumption, price level of USA GDPo in 2011=1	0,37	0,55	0,49
pl_x	Price level of exports, price level of USA GDPo in 2011=1	0,44	0,47	0,07
pl_m	Price level of imports, price level of USA GDPo in 2011=1	0,43	0,45	0,05
pl_n	Price level of the capital stock, price level of USA in 2011=1	0,47	0,50	0,06
pl_k	Price level of the capital services, price level of USA=1	1,40	1,06	0,25

Table 2 – Results of treating the 'No-Empty-Cells' database with the neural network as per equations (1) – (4)

Output variable	Euclidean distance E(X; S_i)	Output variable	Euclidean distance E(X; S_i)
labsh	0,10289643	xr	1,16419328
avh	0,13213112	irr	1,18830309
pl_x	0,25313668	ctfp	1,20714548
hc	0,28314643	csn_r	1,27066942
csn_c	0,30163182	csn_m	1,33272667
pl_m	0,40636264	ccon	1,34108299
rgdpe	0,53029917	emp	1,34595378
delta	0,70944368	ck	1,34647368
rwtfpna	0,81232978	csn_x	1,35027583
rkna	0,85973815	rnna	1,35078629
pl_c	0,9952317	pop	1,35133374
pl_con	0,99815527	cn	1,35752019
pl_g	1,01978919	rdana	1,36035624
pl_da	1,02886881	rconna	1,36354026
csn_i	1,04481571	cgdpn	1,37842923
rtfpna	1,06257424	cda	1,37887019
csn_g	1,07277442	cgdpn	1,38814459
pl_n	1,14136608	pl_i	1,4040277
cwtfp	1,14762207	rgdpna	1,40404285
pl_gdpn	1,14945035	rgdpn	1,41830252
pl_gdpn	1,14945035	pl_k	1,42108981

Figure 1

Table 3 Coefficients of multiple regression with STD(AVH) as explained variable, $N = 3006$, $R^2 = 0,514$

variable	coefficient	std. error	t-statistic	p-value
std(hc)	-0,108	0,021	-5,285	0,000000
std(ctfp)	-0,199	0,016	-12,283	0,000000
std(rkna)	-0,319	0,036	-8,936	0,000000
std(irr)	0,185	0,019	9,63	0,000000
std(pl_con)	-2,145	0,425	-5,05	0,000000
std(pl_da)	-0,291	0,237	-1,227	0,219998
std(pl_gdpo)	-0,337	0,066	-5,141	0,000000
std(pl_c)	2,264	0,288	7,856	0,000000
std(pl_i)	-0,07	0,019	-3,697	0,000222
std(pl_g)	0,307	0,099	3,104	0,001927
std(pl_x)	0,457	0,066	6,888	0,000000
std(pl_m)	-0,182	0,067	-2,734	0,006297
std(pl_n)	-0,107	0,032	-3,315	0,000927
constant	0,	0,013	0,	1,000000

Table 4 Coefficients of multiple regression with STD(LABSH) as explained variable, $N = 3006$, $R^2 = 0,507$

variable	coefficient	std. error	t-statistic	p-value
std(cwtfp)	0,248	0,014	17,495	0,000
std(irr)	-0,633	0,016	-39,477	0,000
constant	0,	0,013	0,	1,000

Table 5 Coefficients of multiple regression with STD(RGDPO) as explained variable, N = 3006, $R^2 = 0,999$

variable	coefficient	std. error	t-statistic	p-value
std(pop)	0,036	0,015	2,447	0,014
std(emp)	-0,047	0,019	-2,437	0,015
std(ccon)	0,042	0,027	1,569	0,117
std(cda)	0,789	0,047	16,649	0,000
std(cn)	0,068	0,013	5,065	0,000
std(ck)	0,025	0,003	7,554	0,000
std(rgdpna)	0,376	0,044	8,55	0,000
std(rconna)	-0,173	0,031	-5,606	0,000
std(rdana)	-0,098	0,055	-1,785	0,074
std(rnna)	-0,019	0,011	-1,668	0,095
constant	0,	0,	0,	1,000

Table 6 Coefficients of multiple regression with STD(PL_K) as explained variable, N = 3006, $R^2 = 0,178$

variable	coefficient	std. error	t-statistic	p-value
std(irr)	0,422	0,037	11,517	0,000
constant	0,	0,017	0,	1,000

Figures

Figure 1

Relative importance of PWT 9.1