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Key words: Probability theory, natural experiments, random experiments

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Introduction

It is often argued that modern econometrics has contributed very little to economics theory, let alone to the development of the economy. The failure of econometric models in predicting the Global Financial Crisis has further cast doubt on the usefulness of macro-econometrics. Nowadays more and more people (including some economists) do not believe macroeconometric modelling results. For example, the Institute for New Economic Thinking is especially against stochastic models. However, grumbling about macroeconometric modelling does little damage to its popularity: various macoreconometric models continue to flood academic journals and universities despite the fact that students are voting against economics with their feet. Therefore, this paper is not to join the chorus of those criticizing the usefulness of macro-econometric, but to

question its validity. The paper tries to answer a simple yet fundamental question: is macro-econometrics theoretically sound?

Macroeconometrics arose from the failure of macroeconomic theory to fit with the real data, and from its inability to use the large amount of macroeconomic time series data. When examined by macroeconomic data, many doctrines in economics appear to be temporary. For example, the Philips Curve broke down in the long run. An economic theory may not be supported by the economic time series data for two reasons. One is that the theory may be wrong; the other is that the economic time series data may not satisfy the 'other things being equal' requirement for an economic theory. Consequently, we cannot verify the correctness of an economic theory based on economic data. The way out of this dilemma was suggested by Haavelmo (1944). In his paper entitled 'The probability approach in econometrics', Haavelmo formally introduced the statistical probability concept into econometrics and suggested a totally new approach to economic study: instead of formulating an economic theory to explain economic phenomena, economists should use historical data to estimate equations and use the equations to predict the future[1]. It appears that Haavelmo suggested a grand plan or a comprehensive approach towards economic research and utilizing time series data. The silver bullet offered by Haavelmo was gladly accepted by economists in need and papers using macroeconometric models flourished in economic journals. By the end of 20th century, time series analysis (macroeconometrics) has virtually become a synonym for macroeconomics.

Although macroeconometrics has developed enormously since 1944, Haavelmo's paper is still the vital foundation for various macroeconometric models. Thus, this paper mainly focuses on discussing the approach suggested by Haavwlmo (1944) and tries to prove that the foundation for macroeconometrics is based on inappropriate assumptions and on logically flawed reasoning. Once the silver bullet accepted by most economists is proven a totally invalid approach, doing economic research in a scientific way is suggested.

[1] Haavelmo (1944) demonstrated in length how to use joint probability function to estimate simultaneous equations and to do projections. This is now the common practice in macroeconometrics. The focus of this paper is not the procedures of macroeconometric modelling but the foundation on which macroeconmetrics relies.

1. The condition of applying statistic theories.

In Chapter III 'Stochastical schemes as basis for econometrics', Haavelmo successfully argued that the probability theory should be applied to economics. He made a valid point by saying that: even in the case of an exact economic relationship or when we say something is certain, we mean the probability nearly equals one. It is absolutely correct that statistic theories should be able to be used in any discipline, provided that the conditions for statistic theories hold. In the case of applying the probability theory, 'random' is a crucial concept which embodies the conditions of statistic theories. We will examine if the conditions related to the 'random' concept hold in macroeconomics.

(1) Conditions for random experiments

The probability theory is based on the concept of 'random experiments'. Haavelmo (1944, p49) correctly stated that 'the notion of random experiments implies, usually, some hypothetical or actual possibility of 'repeating the experiment under approximately the same conditions' (be noted that here 'under approximately the same conditions' is actually very similar to the term 'other things being equal' used in economics). Based on this explanation, correctly implemented surveys are random experiments, so are scientific experiments. It is very obvious that the macroeconomic time series data hardly fit with the concept of 'experiments', let alone 'random experiments'. However, Haavelmo introduced a concept of 'natural experiments', namely, 'the experiments which, so to speak, are products of Nature, and by which the facts come into existence' (Haavelmo, 1944, p50). Even if we view macro time series data as the result of such 'natural experiments', these experiments are not repeated under approximately the same conditions because conditions change significantly over time. Since 'natural experiments' do not satisfy the conditions for 'random experiments', the former cannot be put under the umbrella of 'random experiments'. Thus, it is invalid to apply probability theory to macroeconomic data. Although Haavelmo circumvented the requirement of 'under approximately the same conditions' by including all possible explanatory factors, this approach is problematic both in theory and in practice. We will discuss the consequence of this appraoch in the next section.

(2) Conditions for random variables

'Random variable' is another important concept in applying the probability theory. Haavelmo gave two types of systems of random variables. One refers to 'random sampling' (Haavelmo, 1944, p46). This type is clearly unrelated to macroeconomics because time series are not survey data. The other type refers to 'stochastically independent' variables, which obey the joint elementary probability law:

$p(x_1, x_2,\ldots, x_r) = p_1(x_1)*p_2(x_2)\ldots*p_r(x_r)$

To satisfy the above equation, each of the r variables (x1, x2,…, xr) must have an independent probability function, i.e. must have an independent dimension in space R (so space R is of r-dimension). In other words, the probability function of each variable does not affect the other. How can we be sure whether or not this condition holds? Without a pre-existing theory, the only way to find the answer is to conduct random experiments. However, it is impossible to do random experiment for time series data, so the assumption of a random variable in a macroeconometric model is made based on the need of a macroeconometric model rather than facts.

(3) Is the disturbance random?

The error part, or disturbance, of estimation is vital to statistical models. The prerequisite for valid estimation is that the disturbance is random. In a statistical model, the disturbance is regarded as random because the data come from random experiments. In Macroeconometrics, the assumption of random disturbance (error term) is made without either any theoretic foundation or any experiments conducted. If this assumption made by macro-econometricians does not hold, the entire macroeconometric model is invalid. In fact, time series data come from 'natural experiments', which do not satisfy the condition for random experiments, so there is no foundation to assume the disturbance in a macroeconometric model is random. If we say the assumption of random disturbance in a statistic model is reasonable because of random experiments, the random disturbance in a macroeconometric model is an inappropriate assumption or, essentially, a false claim.

Some econometricians even go further in viewing the uncertainty of the future as random.

It is true that an uncertain event (e.g. cyclones) may 'randomly' happen any time in the future. However, in order to include the future uncertainty in the disturbance one must judge if uncertainty is random according to the 'random' concept in the statistic theory. That is, one must do random experiments. There is no way to do random experiments regarding uncertainty, so the claim of random uncertainty is purely based on macroeconometricians' vague imagination and thus is unscientific.

Here it is useful to discuss the endogeneity test (e.g. Holfman test). To be sure that the estimation is consistent, one needs to make sure that the explanatory variables are not correlated to the disturbance. The endogeneity test is used for this purpose. One may think that, if a model passes the endogeneity test, the disturbance is proven random. The error in this thinking is to treat the 'error term' the same as an 'explanatory variable'. The error term of a regression is directly related to the concept of random experiments, so the conditions for random experiments must be satisfied in order to be sure that the error term is really random.

In short, the entire statistic theory is built on the concept of random experiments, but there is no chance to conduct random experiments in macroeconomics. The so-called natural experiments are not random experiments because the natural experiments do not satisfy the conditions for random experiments. Therefore, there is no foundation for applying statistic theory to macroeconomics. Based on some inappropriate assumptions, which do not satisfy the conditions for statistic theory, macro-econometricians apply probability theory to macroeconomic data. Therefore, it is of no surprise that macroeconometric models may generate invalid and misleading modelling results.

2. Problems with the 'fitting-the-data' approach

In order to apply statistic theory to macroeconomic data, macro-econometricians have to rely on the concept of natural experiments. To satisfy the requirement of 'under approximately the same condition' for random experiments, macro-econometricians have to include in their models all possible factors as explanatory variables. The underlying reasoning is that, if all factors are taken into account in repeated experiments, any changes in the experiment environment become the variables in the model and thus it can

be said that the experiments are done under the same condition. In doing so, the econometricians have no choice but to give up the attempt to form a theory because of the complexity arising from the attempt to include all factors. Macroeconometricians turned around to propose an opposite approach: to build a model to fit the data and use it to predict the future. They thought if a model takes account of all factors it should be able to predict the future. This sounds a grand plan or a super theory if it works, but this fitting-the-data approach has a number of problems.

(1) The grand, complex plan is hard to implement with confidence.

First, the complexity arising from taking care of all factors makes the task unmanageable. Numerous factors may affect the research question concerned. A researcher cannot say he/she has taken into account all possible factors because many factors may be unknown to the researcher. Scientists and statisticians avoid the impossible task of taking account of unknown factors by doing scientific or random experiments under the (approximately) same condition, but macroeconometrians simply claim adamantly, but emptily, that they have included all important factors or that the unknown factors are unimportant. This unscientific claim will invalidate the whole approach. Moreover, the independent variables may influence the dependent variable in a number of ways, so a range of functions can be employed to depict the relationship between dependent and independent variables. Given the large numbers of variables in a model, how could anyone work out the correct function to choose? To make things worse, the interrelationship between independent variables may make the function form even more complicated and thus increases the chance of function misspecification.

For a macroeconomic research question, the possible influencing factors are expected to be more than other research questions, so the task of taking care of all factors is even harder. If a scientist is unable to include all factors, how could an econometrician make such a claim? Macroeconometricans are aware of the severe consequences of omitting important variables and using an incorrect function form, but the critical question facing macroeconometricians is: how can they be sure that these problems have not occurred in a macroeconometric model? Econometricians proposed R-squared or other statistic

criteria (e.g. the Schwarz criterion and Akaike information criterion) as the indicators of omission of important variables and/or function misspecification. However, there is a gap in their reasoning: these indicators may show how close the model fits the data, but provide no guarantee that all important variables have been included and that the correct function form is used.

Second, the 'random' assumptions do not hold. The statistic theory requires that the explanatory variables are random, or stochastically independent in the case of natural experiments. Given the numerous links between macroeconomic variables, this requirement is highly unlikely to be satisfied for all explanatory variables. An econometrician may weaken this requirement by saying that the multicolinearity problem caused by dependence among explanatory variables only affects the estimated coefficients and does not affect the projection results from the model. This argument sounds persuasive but can hardly stand. As will be explained later, a model cannot project the future correctly unless it contains important driving forces and describes accurately how these factors work both currently and in the future.

A random disturbance (error term) is the precondition for a valid estimation but this precondition does not hold in macroeconometrics. In order to claim that 'natural experiments' are random experiments, macroeconometricians have to include all factors in the models. Unable to claim that he/she has included all possible variables in a model, an econometrician may say all unaccounted variables are expressed in the error term. In order for the projection from a macroeconometric model to be valid, one must also interpret the uncertainty in the future as random and assume that it is included in the error term. This leads to enormous pressure being put on the claim that the error term is random. However, this is an assumption always assumed by macro-econometricians but not consistent with the conditions for the probability theory. Given the high possibility of omitting variables (or the impossibility of including all possible variables) and function misspecification, the disturbance is most likely not random. Moreover, given that it is invalid to claim that the uncertainty in the future is statistically random, putting uncertainty in the error term may violate the assumption of the random error term. Thus, the macro-econometric estimations and projections are based on a flawed assumption.

(2) Even if one supposes all the statistical assumptions hold and thus the macro-econometric model is valid for the existing data, the model projection into the future is invalid.

Macroeconometricians believe that if a model can fit the historical data well it will fit the future data well. There are two flaws in this reasoning. One is that, without an accurate understanding of the reality, correct projections cannot be made simply through mimicking reality. A macroeconometric model may fit the data very well but it may not reveal how the influential factors drive the results[2]. If a model does not show correctly how the explanatory factors work currently, it is impossible for the model to show how the factors will work in the future and thus to make a reasonable projection. This reasoning can be shown in the following analogy. Hypothetically, the president of an isolated and technologically-disadvantaged country saw an airplane and desired one, so he asks his people to create one. His people manage to build an airplane that is of the same shape, the same size, same colour, and the same weight, but it has no engine and no electronic system. Do you expect this airplane to fly?

The other flaw in macroeconometricians' reasoning is that it is impossible for a macroeconometric model to include the unknown new variables at a future time. The world is constantly changing so the environment in the future is different from the one for a macroeconometric model estimated from historical data. Even if the best fitting-the-data model can include all possible variables now, it is impossible for it to include the new variables appearing in the future because the variable may be unknown at the present time. From this point of view, a fitting-the-data model can never predict the future successfully because the model does not have the ability to take into account the future changing environment.

Since the fitting-the-data approach cannot predict the future, how can we make a correct projection about the future? Any mechanic models will fail to do so because it cannot

[2] In fact, macroeconometricians are only interested in how to mimic reality and do not care about how the explanatory factors works. This is evident by macroeconometricans' relaxing the assumption of random variables by saying that the multicolleanirity affects estimation results but does not affect projection results.

reveal the factors working both currently and in the future. Thus, the only way to correctly project the future is to study and understand the current situation, uncover the influential factors as well as how they work, and make a projection assuming these factors will work in the same way in the future. A good example of this way of making a projection is the gravity law. After we have understood that the gravity law is the force between any objects in the universe, we can project the movement of the Earth and the moon this year, next year and many years to come. We can also project the movement of other objects like satellites, spaceships, or a bullet. If the future environment changes, we need to work out what are the new influential factors and how they work, and modify our projection accordingly. In short, a projection must be based on a good understanding of the phenomenon, not merely based on mimicking the phenomenon through a mechanic model.

(3) The fitting-the-data approach is prone to be fooled by macroeconomic data.

From its name, the fitting-the-data approach is trying to follow the data, instead of following the logic or one's reasoning. This is a very dangerous practice in macroeconomics because macroeconomic data are generally aggregate data. During the aggregation process, the measurement errors at micro level will be aggregated and thus be magnified. Some macro data are themselves the results from a model. Anyone trying to follow the data may be easily fooled by the measurement errors, and some macroeconometric techniques to purify the data may make this proclivity even more severe. For example, due to the accumulated measurement error during the aggregation, the trends of macro time series are relatively reliable but the variations from the means are not. The common practice in macroeconometrics – de-trending and/or first-differencing – will throw away the reliable information about the data but focus on the unreliable variation. Take the U.S. GDP time series for an example. The annual GDP from 1926 to 2013 is in the magnitude of $US1019.9-16768.1 billion. We take a conservative view to assume a relatively small measurement error, which is 1% of GDP, we have the measurement error for US GDP ranging from $US10.2 to $US167.7 billion. The first difference of the GDP arranges $US56.0 – 604.9 billion. Since the measurement error may increase in the operation of first differencing (e.g. there is a downward

measurement error in the previous year and an upward measurement error in the current year), we again take a conservative view that the measurement errors are unchanged. Even so, the measurement errors could account for as high as 8.7 – 91.9% (average 20.2%) of the first-differenced value (see the last column of the table in appendix). Keeping in mind this magnitude of measurement error, how can anyone trust the modelling results based on the first-differenced or de-trended data? How can the tests based on the variation of data (e.g the unit root tests) be reliable? A cynical person would say this kind of modelling is not a study on macroeconomic data but a model about measurement errors.

Another example of macroeconometricians being fooled by data is spurious regression. There are many examples of spurious regressions. As early as in 1926, Yule (1926) found high nonsense correlations between the proportion of Church of England marriages to all marriages with the standardized mortality during 1866-1911. Dutch statistics showed a positive correlation between the number of storks nesting and the number of human babies born in a series of springs (Sapsford and Jupp, 2006). Yule (1926) attributed the 'nonsense correlations' to the time lag effect, or serial correlations in the disturbance. Following this line, Granger developed an econometric method to test causality, and a large body of literature has been devoted to modelling non-stationary time series. Ironically, few people use their logic – the basic study and analysis tool – to differentiate causality from correlation.

Till now most economists think that they can avoid spurious regression if they can overcome the non-stationary issue and causality issue by employing a non-stationary model and/or the Granger causality test. Is this practice able to overcome the problem of spurious regression? Here we use the power of logical reasoning to find out.

It is true that the correlation between two time series is temporary and thus false if one or both of them are nonstationary because the time series will drift (i.e. random walk) or will explode over time. However, even if a non-stationary model (e.g. cointegration or first-differencing model) can overcome the nonstationary issue, the modeller cannot guarantee that the revealed correlation is not spurious.

Granger correctly pointed out the difference between correlation and causality, but thought a mathematical testing can detect causality. One problem with the Granger causality test is the number of lags used. Theoretically, any number of lags is possible and that number may change over time. It is hard to know the actual number of lags in reality and thus one has no way to select correctly the number of lags for the Ggranger test. So, the test relies on the arbitrary selection of lag numbers. Even with the help of some statistics criteria, e.g. the Schwarz criterion and Akaike information criterion, the arbitrary selection of lag numbers makes the testing very subjective (this problem occurs in any models involving in lag effect). Another problem with the Granger causality test is the measurement errors in macro data. As shown previously, a small the measurement error on original data (e.g. 1% of GDP) could be as high as 91.9% of the first-differenced data (the period by period change). Based on this example, how can we trust the results of the Granger causality test, which is based on the first-differenced data?

More importantly, the biggest problem with the Granger causality test is that the reasoning for the test is flawed. The test assumes that if an earlier change in time series A corresponds to a later change in time series B, A must cause B. While it is true that a cause is always occurring earlier than the consequence, the reverse is not necessarily true. So a logic mistake is embedded in the Granger causality test. This mistake can be easily illustrated by a hypothetical experiment.

Assume that a scientist is experimenting on the impact of temperature on the growth of plants A and B and that, in the selected range of temperature, both plants respond positively to the increase in temperature but plant A is more sensitive to temperature change (i.e. plant A responds faster). As the temperature increases, plant A and B grow faster, so there is causality between temperature and the growth of both plants. Meanwhile, since plant A responds faster to the temperature change, the recorded change in growth of plant A will be always earlier than that for plant B. Therefore, the Granger causality test in this case would conclude that growth of plant A causes the growth of plant B. Apparently, the Granger causality test is flawed and has failed in this case. The only way to test causality is to use our reasoning power.

(4) The fitting-the-data approach disguises the truth and even becomes the obstacle to finding the truth.

As demonstrated previously, the projection of the future cannot be correctly made by mimicking history but can only come about by understanding how the underpinning factors work. So, it is crucial for us to find out how a system works. The fitting-the-data approach makes little contribution to this end; on the contrary, it has in fact prevented us from finding the truth.

First, the fitting-the-data approach points in the direction opposite to what scientists take. The right way to find the truth is shown by scientific experiments. During the experiments, the scientists try to limit the number of variables by changing one variable at a time and keeping other conditions unchanged. In this way, they can find out how this variable affects the results and work out what mathematic function can best describe the impact of this variable. In the fitting-the-data approach, macroeconometricians do the opposite to what scientists do. They try to include all possible variables in a model. If this way of including all factors can find out the truth, there is no need to keep the same experimental conditions in scientific experiments, no need to keep approximately the same condition for random experiments, and no need of 'other things being equal' condition for an economic theory. The well-established protocols in doing scientific experiments or random experiments show that the fitting-the-data approach must be an invalid one.

Second, the complexity of this approach tends to muddle the truth. In order to satisfy the condition for random experiments, the macroeconometricians have to include all possible factors in a model. The model is further complicated by econometricians' attempts to use as-long-as-possible time series data in the hope of increasing the number of observations (and thus the degree of freedom), avoiding the small sample bias, and avoiding the possible spurious regression. Although structure change variables can be added to the model to indicate the changing environment over time, adding structure change variables not only increases the number of variables in the model but also imposes an impossible task of modelling how the structural change variables interact with other variables.

Given numerous possible functions by which a variable may affect the results, the numerous kinds of combined effects of different variables, as well as the changing environment embedded in the long time series, it is extremely difficult (if not impossible) to find out the true mechanism through which the explanatory variables work towards the results. This way of doing research is compromised by complications and thus is a way of disguising the truth, instead of finding it.

Finally, this approach confuses the truth with fitting the data and thus discourages the effort to find the mechanism behind the phenomenon. The aim of the fitting-the-data approach is to find a model which can best fit the existing data. It is believed that if a model can fit the data well it must be close to the truth. This belief is simply an illusion because different mechanisms can lead to the same results (or data). To put it differently, many macroeconometric models can fit the same data very nicely but there is only one truth (e.g. the GDP identity equations, as will be shown in section 4), so how can it be possible that all these models reveal the truth? Due to the existence of relatively large measurement error in macroeconomics and the complex interaction among macroeconomic variables, even the best-fitted model may be not anywhere near the truth. However, the model gives us a false impression that it reflects the truth because it can approximate the existing time series. Under this false impression, economists are complacent with macroeconometric modelling results and have no intention of finding the truth.

In short, the fitting-the-data approach is a grand but unscientific way to do research because the approach is overwhelmed by complexity. The approach is also very harmful in that it highjacks the objectives of research from finding the truth to fitting the data. The approach muddles with truth, disguises the truth, and gives a false impression of close-to-truth, which make people complacent and stop their searching for truth.

3. Is it possible to have a permanent economic law?

Haavelmo (1944) lamented many times that, no law in economics is as permanent and universal as those obtained in the natural sciences. In his mind, a universal permanent law would make economics more like natural science, i.e. more scientific. This formed part of

his motives for forming a constant universal economic law which can explain everything or, at least, the existing data. In this section, we discuss the possibility and the needs to develop a permanent economic law. We start with laws in natural science.

(1) Conditions and laws in natural sciences.

Laws in natural sciences are viewed as universal and permanent, for example, the gravity law applies to anywhere in the universe and can explain the movement of very remote stars and planets. The law worked millions of years ago and will continue to work in the future. However, any laws or theories have conditions for them to work and this universal gravity law is of no exception. First, the gravity law is not the law governing the micro world. Current physics shows many other kinds of forces among tiny particles in the micro world. Although gravity still exists in the micro world, it is very weak so it cannot be used to explain the micro world. Second, the gravity law works under the condition that there is no transformation between energy and mass. When Einstein's equation of mass-energy relation is introduced, the whole gravity law has to change. Last, although the gravity law can explain the movement of stars and planets, it cannot explain the universe as a whole. It is said even the founder of the gravity law Newton himself was puzzled by the question – why the Earth moves in the first place, and he had to turn to God for the answer. Moreover, if the gravity law is the governing law of the universe, the stars and planets should be pulled closer and the universe should shrink over time. However, the scientific evidence shows that the universe is expanding.

As the world is changing constantly, any laws and theories have to adapt to the changing conditions. The gravity law can predict the orbits that a planet revolves around the star, but there is evidence that, over time, planets (e.g. the Earth) are drifting away from the Sun. So the predictions from the gravity law have to be revised after a certain period. To put it differently, the gravity law is based on Kepler's Laws on planetary orbit, which is based on hundreds of years of astronomic observation data. If this observation continues for thousands years and the physicist is unaware of the changing conditions, he/she must conclude that there is no permanent (or consistent) planetary orbit and thus there is no way of finding either Kepler's law or the gravity law. In addition, the gravity law also

needs to evolve as science progresses. As the evidence of mass energy transformation surfaces, the gravity law has had to be replaced by quantum physics.

(2) The nature of social science.

Compared with the laws in natural science, the laws in social science (including economics) look much less splendid. Laws in social science work on a much smaller scale and often change over time. A good example of this in economics is the Phillip's curve – the curve works well in the short run but it shifts left or right in the long run. The temporality of the laws in social science may make social science look less scientific, but it actually reflects the nature of social science. Social science is the science related to human activities or the science studying human behaviour. Human beings, as the most intelligent creature on Earth, can learn and react. The conditions for a law in social science may not be satisfied when human behavior changes.

In the case of the Phillip's curve, the inverse relationship between inflation and unemployment in the short run is perfectly understandable: higher inflation means higher demand for goods and services, more job opportunities, and thus less unemployment. In the long run, however, the monetary and fiscal policy may change and this can cause a change in inflation, so a high inflation does not necessarily mean high final demand and more job opportunities. With the lessons learned from the Great Depression, Keynesian economists advocated expansionary monetary and fiscal policy to stimulate growth. However, the expansionary policy did not address the fundamental cause of economic recessions, so it led to a high inflation rate but little economic growth, i.e. stagflation. In this case, a high inflation rate will coexist with high unemployment and thus the Philip's curve will break down. This explains why the Phillip's curve shifted to the right during the 1970s.

The need to take into account the reaction of the objects studied is not unique either in economics or in other social science. The reaction of studied objects also happens in natural science such as in biology and in medical science. It is not a surprise to find that a plant may change its appearance in a new environment, or that some animals change their behavior as the environment changes. The alarming example in medical science is the

super bugs. Ordinary antibiotics such as penicillin normally work well in killing bacteria, but now some germs have evolved and are immune to common antibiotics. This causes dire situations where we cannot control the spread of some diseases. The notable cases include the bird flu, SARs, and recently Ebola. In these cases, it is not useful to lament that penicillin does not work, we need to find out why the bacteria evolve and how to prevent them from continuing to evolve while, on the other hand, finding new antibiotics which can kill these superbugs.

From the discussion above, it is safe to say that there are no such things as permanent and universal laws either in the natural or social sciences. Even a law as permanent and universal as the gravity law has its conditions and the law has to evolve over time. The economic laws are less permanent and less universal because of the nature of social science – the conditions of a law in social science are often broken due to the reaction of research objects. Consequently, there is neither the possibility nor the need to have a permanent and universal law in economics. The right attitude towards economics laws is not to pursue a permanent and/or universal law, but to be conscious about the conditions for each law and to take into account the changing environment. If the conditions for an economic law do not hold due to the change of circumstances, one needs to modify that law to reflect the new environment or to form a new law or advance the economic theory.

4. The performance of Macroeconometric modelling: a demonstration

To demonstrate the performance of macroeconometric models, the author uses the US macro time series data 1969-2013 (see the table in the appendix) to estimate the GDP identity, i.e. the expenditure and income sides of GDP. Since there are some statistic discrepancies in the two sides of the GDP, one must choose one side as the GDP value. The author chooses the income side of the GDP. Based on the 1-lagged GDP and the variables on both sides of GDP, the author estimated 7 models. The estimation results for various models are shown in Table 1. For the benefit of non-econometricians, the author has not only listed the coefficient and standard error for each variable, but also listed the p-value.

Table 1: estimation results for US GDP 1969-2013*

Explanatory variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
1-Lagged GDP	NA	NA	1.027835 (.0062792) p=0.003	NA	-.0033368 (.0571678) p=0.954	NA	NA
Constant	.0100158 (.0290984) p=0.732	81.31557 (27.25534) p=0.005	167.7843 (53.17188) p=0.000	-.0072479 (.0539686) p=0.894	82.9972 (29.57229) p=0.008	-44.1798 (21.16042) p=0.043	51.04608 (13.92943) p=0.001
Wage	.9998437 (.0000685) p=0.000	NA	NA	.9999421 (.0003693) p=0.000	NA	1.311298 (.0320946) p=0.000	.9197758 (.0628478) p=0.000
Tax	1.00024 (.0008111) p=0.000	NA	NA	1.000116 (.0013469) p=0.000	NA	NA	NA
Profit	1.000112 (.0000859) p=0.000	NA	NA	1.000202 (.0002734) p=0.000	NA	1.231101 (.0700907) p=0.000	.8337058 (.0588025) p=0.000
Fixed Capital	1.00028 (.0002497) p=0.000	NA	NA	.9998864 (.0005665 p=0.000	NA	NA	NA
Consumption	NA	1.275733 (.0452806) p=0.000	NA	-.0000493 (.0004116) p=0.905	1.281519 (.0851167) p=0.000	NA	.4509562 (.0564406) p=0.000
Investment	NA	.7793903 (.0635759) p=0.000	NA	-.0000775 (.0003573) p=0.830	.7772844 (.0682467) p=0.000	NA	-.0225597 (.0461778) p=0.628
Net exports	NA	.6962019 (.0853013) p=0.000	NA	-.0001073 (.0003221) p=0.741	.694964 (.0954259) p=0.000	NA	NA
Government Spending	NA	.161384 (.1271703) p=0.212	NA	.0001931 (.0003509) p=0.586	.1587255 (.1367049) p=0.253	NA	NA
Adjusted R-squared	1.0000	0.9999	0.9984	1.0000	0.9999	0.9998	1.0000

Time series data are from the Bureau of Economic Analysis (http://www.bea.gov//national/nipaweb/DownSS2.asp). The estimation is performed using Stata software. The table lists the coefficient, standard error (in parentheses), and the p-value for each explanatory variable. The p-value indicates the chance of rejecting the hypothesis that the variable is significant.

The estimation results for model 1 are perfect: the adjusted R-squared is 1, all variables on the income side of the GDP are extremely significant (p=0.000) and the coefficients are extremely close to 1. The coefficient on the constant is close to zero with very high p-value (p=0.732). This are exactly what is predicted by the GDP identity: GDP=Wage

+Tax + Profit + Capital Formation. One may hail that the macroeconometric model works! However, this is not the usual case in macroeconometric modelling and the model is working because the assumptions of the model held. With perfect theoretic knowledge we know that all variables are included in the model so the conditions for random experiments hold. We also know perfectly well that we have the right function for the model. More importantly, the data perfectly fit in the GDP identity equation except for very tiny rounding errors (about US$0.1 billion for a magnitude of US$1018-16980 billion GDP) for some years, so the OLS mechanism will find the best fit.

Model 2 estimates the GDP identity on the expenditure side: GDP = Consumption + Investment + Net Export + Government Spending. With perfect knowledge, this model also includes all variables and uses the right function. However, the data do not fit in the equation closely because of the statistic discrepancy (measurement error) on both sides of the GDP. The measurement error causes much damage to the estimation. Although R-squared is still very high (0.9999) and most explanatory variables are significant, the results are quite far away from the truth: all coefficients are not close to 1. The contribution of consumption is overestimated while the contribution of investment and net export is underestimated; the contribution of government spending to the GDP will be discounted by more than 80%; effectively it is insignificant even if one uses the 10% p-value as a benchmark of rejection of significance of government spending. The constant should be zero, but modelling results show it is very significant.

Model 3 estimates the impact of a lagged GDP on current GDP – using lagged variables is a common practice in time series modelling. The estimation shows a very high R-squared (0.9984) and a very significant impact of past GDP. In fact the coefficient of 1-lagged GDP is close to (or slightly greater than) 1. This confirms the view that most macroeconomic variables are non-stationary. But the unit root tests on GDP and other variables are mixed, depending on what type of test is employed. If one believes these variables are non-stationary and thus employs a first-differenced model or a cointegrated VAR model, the results may interest macroeconometricans, but definitely they are going to be further away from the truth because there is no dynamics in the GDP identity equation.

Model 4 includes all variables from both sides of GDP. This exercise assumes that we have no knowledge of what variable is relevant or important so we have to include all possible variables. The estimation results show that the coefficients on income-side variables are very close to 1 while those on expenditure-side variables are very close to zero. Since the coefficients on income-side variables are quite close to the results in Model 1, one may conclude that the irrelevant variables added to the model will not change the modelling results. However, here the expenditure-side variables are not irrelevant variables – they are components of the GDP! Their coefficients are zero simply because the model has already found the best fit, so they become redundant variables. This reasoning is confirmed by the fact that when the expenditure side of GDP values are used as the values for dependent variables, the expenditure side of GDP components become very significant with coefficients close to 1 while the income side of GDP components are insignificant. Hence, these results demonstrate that an econometric model cannot find which variables are relevant or important but can only suggest which variables can fit the data better. In other words, an econometric model may help you to find the truth, but it is unable to find the truth for you.

Models 5-7 show different combinations of variable selections. Model 5 includes the 1-lagged GDP and expenditure-side variables. The results show that the coefficients for expenditure-side variables are very similar to the results from Model 2, while the lagged GDP becomes insignificant. Again, this result does not indicate the expenditure side variables are more important than the lagged GDP, but only shows that the expenditure side variable can fit the data better than the lagged GDP. Model 6 keeps the relatively more important variables on the expenditure side – wage and profit – but excludes the relatively less important variables – tax and fixed capital formation. The results show the significant overstatement of the contribution of wage and profit. This is simply the consequence of omitting variables in macroeconometric models, but this model is the likely case in macroeconometric modelling, i.e. no one has perfect knowledge to include all variables. Model 7 includes the most important variables from both sides of the GDP, namely, wage, profit, consumption and investment. The estimation results do not make sense in economics: wage, profit and consumption make a discounted contribution to GDP (the coefficients for these variables are significantly less than 1) but investment

contributes negatively (albeit insignificantly) to the GDP.

From this illustrative estimation exercise we see that, if the conditions for statistical theory hold, a statistical model works well (e.g. Model 1). However, this is the unlikely case in macroeconometrics because we do not have the perfect knowledge about the factors involved and the correct functions to be used, and because the macroeconomic data are not accurate. From the performance of Model 5-7 we can imagine how misleading a macroeconometric model can be. The estimation results can be even worse considering the possibility of misspecification of function forms. In short, a macroeconometric model is most likely unable to find the truth due to measurement errors in data (e.g. Model 2), inability to include all possible factors (e.g. Model 5, 6, 7), interference between independent variables (Model 5, 7), and misspecification of function form.

5. Concluding remarks

From our discussion and the demonstrative example of the GDP estimation, it is clear that the fitting-the-data approach suggested by Haavelmo (1944) and now popularly used in macroeconomics is an unscientific way to do research for a number of reasons. First, the conditions for the required application of the statistic theory do not hold. The inability to include all factors in a model means that natural experiments do not satisfy the conditions for random experiments, so the assumption of random disturbance in macroeconometrics is false and the estimation if invalid. Second, there is a fundamental logic flaw in its reasoning that, if a model can mimic the past well (fitting in the time series data), it has the power to predict the future, even without a good understanding of what is the driving force and how it works. This logic flaw was highlighted by the econometricians' failure to predict the GFC. Third, the grand approach is overwhelmed by complexity and is unable to find out accurately what factors are involved and how they work. This way of doing research is potentially detrimental because it hijacks the goal of doing research – finding the truth – and replaces it with a mechanical fitting of the data and, more importantly, because the approach ignores or downplays the logic reasoning power of human beings – the fundamental tool in finding the truth.

Since a permanent and universal law does not exist in either natural or social science, it is impossible as well as ridiculous to pursue such a law in economics. Every law (theory) has its conditions. When the conditions are not met, the law will break down. Every law (theory) will also evolve over time either due to the change in the environment or due to the advent of new evidence. Generally, the laws in social science (including economics) are less permanent and less universal than the laws in natural science. This is because the reaction of human beings tends to break the conditions for the laws. Thus, a less permanent and less universal law does not indicate that social science is less advanced than natural science.

This paper rejects the fitting-the-data approach, namely, an approach which tries to include all possible explanatory variables in a model and tries to mimic reality instead of understanding it. However, the paper does not reject indiscriminately all application of probability theory, nor reject the use of multi-regression in macroeconomics. For example, if the time series is not long and thus there is no significant change in the macro environment, or if the change in macro environment is irrelevant to the research question (e.g. the GDP identity demonstrated on this paper), the natural experiments can be viewed as conducted under approximately the same condition and thus the probability law and multi-regression are applicable. It is often argued whether one should only allow in the model the variables suggested by theory or one should include all significant variables suggested by data. From the author's point of view, both approaches are valid. The first approach uses econometrics to ratify the theory while the second approach can be used to form a theory. The important thing for either approach is that a regression needs to satisfy the conditions of applying probability theory and that the goal of regression is to find the truth behind the data.

Furthermore, the rejection of the fitting-the-data approach illustrates to us the valid way to do economic research. That is, to study the economic phenomena, find the truth or the driving forces behind them, and form a law (or theory) based on these driving forces. Assuming the conditions for the law are satisfied and thus the driving forces are continuing to work in the future, one can use the law (or theory) to project the future. The researchers should pay much attention to the conditions for the law and to the changing

environment. When the environment changes, the conditions for the law may not hold and thus the data may not support the law. In this case, we need to either modify the law or to develop a new one.

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Appendix: The expenditure and income sides of US GDP

Year	GDP	Wage	Tax	Profit	Fixed Capital	Consum	invest	Net Exports	Gov	dGDP	Measurement Error (%) (1% of GDP)/dGDP
1969	1,018.3	586.0	79.4	228.1	124.9	604.5	173.6	1.4	240.4		
1970	1,070.5	625.1	86.6	222.0	136.8	647.7	170.1	3.9	254.2	52.2	20.5
1971	1,158.3	667.0	95.8	246.6	148.9	701.0	196.8	0.7	269.3	87.8	13.2
1972	1,275.3	733.6	101.3	279.5	160.9	769.4	228.1	-3.4	288.2	117.0	10.9
1973	1,422.4	815.1	112.0	317.3	178.1	851.1	266.9	4.1	306.4	147.1	9.7
1974	1,541.4	890.3	121.6	323.3	206.2	932.0	274.5	-0.8	343.1	119.0	13.0
1975	1,675.7	950.2	130.8	357.1	237.5	1,032.8	257.3	16.0	382.9	134.3	12.5
1976	1,857.1	1,051.3	141.3	405.4	259.2	1,150.2	323.2	-1.6	405.8	181.4	10.2
1977	2,066.7	1,169.0	152.6	456.8	288.3	1,276.7	396.6	-23.0	435.8	209.6	9.9
1978	2,333.4	1,320.3	162.0	526.1	325.1	1,426.2	478.4	-25.4	477.4	266.7	8.7
1979	2,587.4	1,481.1	171.6	563.6	371.1	1,589.5	539.7	-22.6	525.5	254.0	10.2
1980	2,818.6	1,626.3	190.5	575.7	426.0	1,754.6	530.1	-13.0	590.8	231.2	12.2
1981	3,174.2	1,795.4	224.1	669.6	485.0	1,937.5	631.2	-12.6	654.7	355.6	8.9
1982	3,338.2	1,894.5	225.9	683.5	534.3	2,073.9	581.0	-20.0	710.0	164.0	20.4
1983	3,584.0	2,014.1	242.0	767.4	560.5	2,286.5	637.5	-51.6	765.7	245.8	14.6
1984	4,002.0	2,217.6	268.7	921.4	594.3	2,498.2	820.1	-102.7	825.2	418.0	9.6
1985	4,295.5	2,389.2	286.7	982.9	636.7	2,722.7	829.6	-114.0	908.4	293.5	14.6
1986	4,513.4	2,545.6	298.5	987.1	682.2	2,898.4	849.1	-131.9	974.5	217.9	20.7
1987	4,829.7	2,725.7	317.2	1,058.8	728.0	3,092.1	892.2	-144.8	1,030.8	316.3	15.3
1988	5,253.1	2,950.9	345.0	1,174.8	782.4	3,346.9	937.0	-109.4	1,078.2	423.4	12.4
1989	5,593.5	3,143.9	371.5	1,242.1	836.1	3,592.8	999.7	-86.7	1,151.9	340.4	16.4
1990	5,888.2	3,345.0	398.0	1,258.4	886.8	3,825.6	993.5	-77.8	1,238.4	294.7	20.0
1991	6,085.7	3,454.7	429.6	1,270.2	931.1	3,960.2	944.3	-28.6	1,298.2	197.5	30.8
1992	6,428.4	3,674.1	453.3	1,341.3	959.7	4,215.7	1,013.0	-34.7	1,345.4	342.7	18.8
1993	6,726.4	3,824.0	466.4	1,432.4	1,003.6	4,471.0	1,106.8	-65.2	1,366.1	298.0	22.6
1994	7,171.9	4,014.1	512.7	1,589.5	1,055.6	4,741.0	1,256.5	-92.5	1,403.7	445.5	16.1
1995	7,573.5	4,206.7	523.1	1,720.9	1,122.8	4,984.2	1,317.5	-89.8	1,452.2	401.6	18.9
1996	8,043.6	4,426.2	545.6	1,895.9	1,176.0	5,268.1	1,432.1	-96.4	1,496.4	470.1	17.1
1997	8,596.2	4,719.1	577.8	2,059.4	1,240.0	5,560.7	1,595.6	-102.0	1,554.2	552.6	15.6
1998	9,149.3	5,082.4	603.1	2,153.6	1,310.3	5,903.0	1,735.3	-162.7	1,613.5	553.1	16.5
1999	9,698.1	5,417.5	628.4	2,251.4	1,400.9	6,307.0	1,884.2	-256.6	1,726.0	548.8	17.7
2000	10,384.3	5,863.1	662.8	2,344.2	1,514.2	6,792.4	2,033.8	-375.8	1,834.4	686.2	15.1
2001	10,736.8	6,053.8	669.0	2,410.1	1,604.0	7,103.1	1,928.6	-368.7	1,958.8	352.5	30.5
2002	11,050.3	6,149.7	721.2	2,517.3	1,662.1	7,384.1	1,925.0	-426.5	2,094.9	313.5	35.2
2003	11,524.3	6,372.7	758.9	2,665.4	1,727.2	7,765.5	2,027.9	-503.6	2,220.8	474.0	24.3
2004	12,283.5	6,748.8	817.5	2,885.5	1,831.7	8,260.0	2,276.7	-619.2	2,357.4	759.2	16.2
2005	13,129.2	7,097.9	873.6	3,175.7	1,982.0	8,794.1	2,527.1	-721.2	2,493.7	845.7	15.5
2006	14,073.2	7,513.7	940.4	3,483.0	2,136.0	9,304.0	2,680.6	-771.0	2,642.2	944.0	14.9
2007	14,460.1	7,908.8	980.0	3,307.0	2,264.4	9,750.5	2,643.7	-718.6	2,801.9	386.9	37.4
2008	14,619.2	8,090.0	989.3	3,176.5	2,363.4	10,013.6	2,424.8	-723.1	3,003.2	159.1	91.9
2009	14,343.4	7,795.7	967.8	3,211.6	2,368.4	9,847.0	1,878.1	-395.5	3,089.1	-275.8	-52.0
2010	14,915.2	7,969.5	1,001.2	3,562.8	2,381.6	10,202.2	2,100.8	-512.7	3,174.0	571.8	26.1
2011	15,556.3	8,277.1	1,042.5	3,785.9	2,450.6	10,689.3	2,239.9	-580.0	3,168.7	641.1	24.3
2012	16,372.3	8,614.9	1,074.0	4,153.2	2,530.2	11,083.1	2,479.2	-568.3	3,169.2	816.0	20.1
2013	16,980.0	8,853.6	1,102.2	4,396.8	2,627.2	11,484.3	2,648.0	-508.2	3,143.9	607.7	27.9

Source: except the last two columns, the data are from Bureau of Economic Analysis (http://www.bea.gov//national/nipaweb/DownSS2.asp).