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ARE WE MITIGATING UNJUSTIFIED THE RANDOMNESS OF THE ECONOMIC REALITY BY SELECTING 'THE APPROPRATE MODEL'?[*]

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Abstract

The main goal of this manuscript is to discuss some of the most important limitations of the quantitative modelling and provide therefore an overview of the risks involve by the usage of forecasts generated with the help of such models. The obvious question that we need to ask ourselves is if the economic reality really is something which can be squeezed into quantitative models or everything is just a sequence of random events which sometimes, for carefully selected subsets of data, seem to follow some "predictable" patterns. For the purpose of bringing forward evidence supporting that "real life randomness" might seem predictable an experiment using 100 randomly generated variables, with 10000 individual values each, is conducted. Even though the initial variables are uncorrelated for some subsets of data we identify notable correlations finding therefore information where, in fact, there is none. Therefore, it is mandatory that limitations implied by quantitative modelling need to be regarded with the required caution whenever they are used.

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1. Introduction

A model is a theoretical construct representing economic processes using a set of variables and a set of logical and/or quantitative relationships between them. More exactly, an economic model is a simplified description of reality, designed to yield hypotheses, about economic behavior, that can be tested. An important feature of an economic model is that it is necessarily subjective in design because there are no objective measures of economic outcome.

All economic models, no matter how complicated, are subjective approximations of reality, designed to explain observed phenomena. It follows that the model's predictions must be tempered by the randomness of the underlying data it seeks to explain and by the validity of the theories used to derive its equations.

A good example is the ongoing debate over existing models' failure to predict or untangle the reasons for the recent global financial crisis. Insufficient attention to the links between overall demand, wealth, and — in particular — excessive financial risk taking has been blamed.

What everybody should bear in mind is that no economic model can be a perfect description of reality. But the very process of constructing, testing, and revising models forces economists and policymakers to tighten their views about how an economy works. This in turn promotes scientific debate over what drives economic behavior and what should (or should not) be done to deal with market failures.

2. General framework and main limitations of quantitative modelling

The main characteristics of an economic quantitative model reveal its most important limitations which are sometimes (most of the times) mitigated by researchers which pursue "the truth" behind different sequences of history. Therefore, the simplification (oversimplification) of reality is used most of the times with the clear purpose of fitting a very complex reality in the constraints of a model which needs to be facile for the human mind to comprehend. Consequently, this process involves discarding all those aspects which seem meaningless in the constraints of the proposed model even though they might have been exactly those elements which have shaped the reality. Such an example is represented by outlier values which are discarded most of the time when quantitative models are constructed, due to the fact that they do not fit anymore in the "oversimplified reality" of the selected model. By doing so, little parts of reality are lost and the key question is: were those little parts exactly the key parts or were they just some random useless add-ons? What is dangerous regarding the previously described mechanism is the fact that economy is subdued by the unstoppable passing of time and unlike phenomena studied by physics cannot be reproduced in laboratories. Thereby, finding the answer to the above question is virtually impossible and so, selecting "the appropriate model" becomes a game of chance where in the end you do not know if you won or lost ("winning means describing the true reality and loosing should be interpreted as describing a flawed reality").

By consequence, we need to ask ourselves if the economic reality really is something which can be squeezed into quantitative models or everything is just a sequence of random events which sometimes, for carefully selected subsets of data, seem to follow some predictable patterns.

The second important aspect that researchers need to take into consideration is the effect of the quantitative models they bring forward. Even though, most researchers are aware of the important limitations of the models they propose, they need to make sure that their full message, including limitations, goes across to the interested reader. They always need to have in mind that the main purpose of the research they conduct is to shed light on the unknown and, finally, to help policy makers construct instruments and policies that will "improve" different economic ecosystems. Thus, by finding patterns, by identifying connections and constructing explanations, researchers help the world understand the hidden mechanisms of the economy and are, therefore, important parts of the entire economic ecosystem. The main "invisible" threat that they bring together with their knowledge is represented by the "underestimation" of the complexity of the economic mechanism. Consequently we owe us at least to be aware of the following question: **Is quantitative modeling just a scientific method to tailor the reality in order to increase the level of trust of the economic agents (private and public) by diminishing artificially the randomness of real life events?**

When constructing different models, researchers identify different associations between different phenomena and use these relationships to explain previously constructed theories or to forge new ones. By knowing the complexity of the economic ecosystem it is near to impossible not to identify these kind of relationships for different time periods and for certain units. Moreover, each phenomenon needs to be measured and, in most of the cases, different measurements are available and selecting the "appropriate" one is just part of the research process. And thus, the "appropriate" proxy is most of the times the one that can help one put the pieces of the puzzle together.

By navigating this complex and dangerous waters of the selection process, we need a line of defense and luckily we have one and that is called "logic". Unfortunately, very motivated human minds can twist logic and common sense in very strange ways, as long as it serves a purpose. Moreover, skilled ones can even make those strange twists seem very plausible as they are mirror reflections of a foggier reality which starts to be less and less foggier as it seemed in the beginning.

By transforming data, by selecting the adequate proxy and by eliminating outliers, are researchers doing nothing more than seeing correlations where there is nothing more than pure randomness and by consequence fabricating a utopic reality?

The representation of this trap of quantitative modelling, namely identifying relationships where in fact there is none, is represented by the pursuit of statistical significance which is a mandatory characteristic for results which need to become feasible instruments for the policymakers. For achieving statistical significance, one uses all the available tools which include, among others, exactly: selecting the appropriate proxy, transforming the available data and eliminating the outlier values. Therefore, the question that needs to be asked is: **by trying to fit the model and by pursuing statistical significance are not researchers increasing the type one error (alfa – significance level) unjustified?**

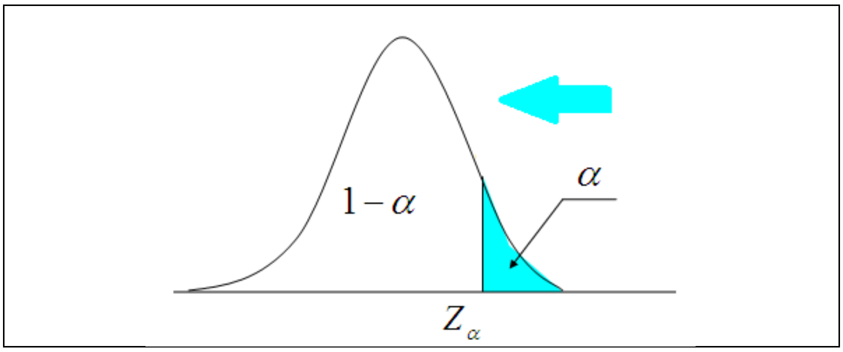

Figure 1. Significance level in a one sided z-test.

Another key limitation of the quantitative modeling (recognized by the entire research community) is that all models are useful as long as the future is a carbon copy of the past. The question is if nowadays we should consider this hypothesis as still being solid enough? This complex mechanism which is the economy is changing swiftly nowadays and does not seen to be frozen in a theoretical equilibrium. Moreover, "the meaningful" research becomes embedded in policies which have the clear purpose of mitigating the errors of the past and, by doing so, altering exactly the characteristics of the past which are preconditions of the validity of results obtained with the help of different models. Therefore, we say that our instrument is useful as long as the future mirrors the past but on the other hand we use the instrument to directly modify the future.

By working with data which describe phenomena which are at the time of the process unrepeatable history, one gets to observe both the phenomenon and its outcomes which is an impossible act for all his ancestors. In this way, he becomes close to a puzzle solver which has "almost" all pieces and, moreover, he knows which the needed result is. However, due to the fact that his ancestors have used quantitative modelling, he no longer knows if the mechanism of constructing the puzzle he will identify is useful outside the history book.

The present is more like a large pile of puzzle pieces, from different pictures randomly mixed together. Also, important to state is the fact that there are no instructions of how to construct the puzzle and there is no image of the correct result. By consequence, even though some pieces seem to fit together, the image is not that clear until "logic" and "common sense" give a hand.

Therefore, by using the historical approach, are not the scientists just fitting the data and the model so that they can explain a reality which for their predecessors was totally unpredictable? And by doing so are they not just diminishing unjustified the randomness of the future and, as a direct consequence, persuade practitioners to take risks that are in reality unacceptable?

3. Theoretical example mirroring a "potential" reality.

3.1. Research goal

The main goal of this still rough research is to provide an empirical description of the limitations implied by the economic quantitative modelling. The method proposed in this manuscript relies on providing a quantitative measure of the probability to identify statistical correlations between totally uncorrelated random variables, when using only parts of these time series. The usage of this mechanism is considered to be an adequate representation of the reality, where researchers can only use sets of data which measure only some finite parts of different phenomena and, therefore, they are not witnessing the entire reality which might lead to totally different findings.

3.2. Methodology and data issues

In order to bring forward evidence supporting the previously described limitations of the quantitative modelling (mainly related with the general validity of the obtained results) the following experiment was conducted:

In the first phase, 100 random variables were generated using www.random.org, where randomness comes from atmospheric noise which might be considered as a better alternative to the pseudo-random number algorithms typically used in computer programs. Each individual variable contains 10000 integers with values between 1 and 10000, randomly distributed.

In the second step, correlation coefficients were computed for each group of two variables (50 groups of two variables were constructed) so that they are presented as different potential "realities" where two phenomena are totally (linear) uncorrelated.

In the third phase, correlations were computed between subsamples of these variables (subsamples selected for each group). There were selected subsamples of 50 consecutive numbers. All potential combinations of these subsamples (using a chronological order) were included in the analysis.

The main limitation implied by the proposed approach is the short time series (only 50 observations) included in the analysis. These limitation will be mitigated in future studies by including larger subsets of numbers in the analysis (100, 200, 500, 1000 consecutive numbers). However, this limitation does not seem that important any longer, when we think that most of the practical cases imply the usage of small data sets because of different reasons.

4. Empirical results

As described in the previous section, after the generation of the random variables, 50 pairs of two random variables were constructed and subsamples of 50 consecutive elements were selected for both of them. Thus, 9951 combinations were generated for each of the 50 pairs and for all of these combinations the correlation (using the Pearson linear correlation coefficient – which is very restrictive) was measured (therefore, the correlation was computed for 497550 combinations of variables with a size of fifty elements). The aggregated results are presented in table number 1, where the correlation coefficients are grouped in four intervals. Only values over the 0.2 threshold were taken into consideration due to the fact that only correlation above this value are noticeable values (and might be also considered statistically significant for certain significance levels).

The correlation coefficients for the initial 50 pairs of the randomly generated variables (where each variable included the 10000 randomly generated values) ranged from -0.0201 to 0.0187. Therefore, it is obvious that there is no notable correlation among these variables and the hypothesis stating the existence of no linear correlation might be accepted.

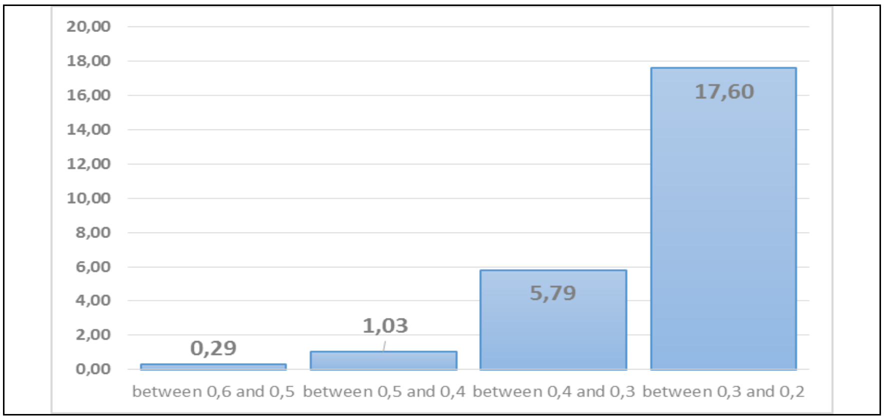

Figure 2. The maximum percentage of correlations between the 9951 pairs of variables for the 50 cases. (Author's work)

As displayed in Figure 2, for one of the 50 pairs, 0.29% of the 9951 combinations display correlations between 0.5 and 0.6 (absolute values) even though the initial variables represent phenomena that are obviously uncorrelated. Correlations between 0.4 and 0.3 were displayed by maximum 1.03% of the combinations of variables for one of the 50 sets of 9951 correlation coefficients. When lowering the threshold to 0.2, we see that we have a maximum of almost 17.6% of the combinations (for one of the 50 cases) displaying values of the correlation coefficients between 0.2 and 0.3.

Analyzing the results displayed in the table it becomes obvious that there are evidence which might support the hypothesis that correlations might be identified between different phenomena where in fact there is nothing more than pure randomness. The identification of these correlations might be sourced in reality from each of the situations described in the general framework section.

Table 1. Aggregated results of the correlations between samples of 50 consecutive numbers

Correlations (absolute values)	Average % of correlations per 9951 combinations	St. dev. (%)	Minimum % of correlations per 9951 combinations
between 0,6 and 0,5	0,02	0,05	0,00
between 0,5 and 0,4	0,38	0,25	0,08
between 0,4 and 0,3	3,07	0,91	1,25
between 0,3 and 0,2	12,96	1,57	9,78

Author's work

Thereby, in the economic world, it is enough to follow the next sequence of steps in order to identify relationships and connections where in fact there is nothing to identify:

1. Identify such correlations (only on historical data and usually on subsets of data describing a significantly larger phenomenon).
2. Use some theoretical background, which is heavily supported by a puzzle which is severely distorted by a subjective understanding of history.
3. Manufacture clever and skillful explanations (which ignore the facts dismissing the findings from point 1) which support the quantitative findings.

By following the procedure presented above, a dedicated researcher, using both empirical evidence and theoretical background, will manage to find an explanation for "nothing". Moreover, if his entire construction has "common sense" it will probably end up by being accepted by his peers.

Furthermore, if such "findings" pile up (three to four different sources are more than enough), their propensity of becoming "knowledge" increases and they even have the potential to become background of some practical measures developed by policymakers.

Finally I might conclude that this is one possibility to fabricate utopic realities using some skillful gathered "evidence".

5. Conclusion

It is common knowledge that all theoretical models are simplified versions of a very complex reality and, therefore, they are very subjective versions of the before mentioned real thing. This is the first limitation of this process that might bring unexpected and unwanted problems when using the results obtained employing this type of quantitative models.

Even though, the theoretical models are, in most cases, flawed, they are the best tools that mankind has today when trying to diminish the uncertainty of the future. Therefore, it is mandatory that before using an approach based on quantitative models, with the purpose of forecasting the future, great caution should be involved. Another important aspect that needs to be taken into consideration is the magnitude of the risks involved and not their probability. By not minding this aspect, or worse, by doing the opposite, practitioners tend to use results obtained from quantitative models and take risks with enormous consequences only because of) the fact that they are highly improbable.

Therefore, whenever using quantitative models constructed on historical data with the purpose of forecasting future events, the entire activity needs to be done with great caution and both the magnitude of the involved consequences and the occurrence probability of the events need to be analyzed.

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