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NEW ANALYTICAL TOOLS AND TECHNIQUES TO BETTER UNDERSTAND SYSTEMS

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This note discusses the development, experimentation and dissemination of new analytical models and methods to understand the complex systems that characterise the economy, society, and environment and their inter-relations. It outlines the potential policy contributions of agent-based models (and econophysics), machine learning and neuroeconomics. The paper concludes with details on experiments explored through the NAEC Innovation LAB (a joint initiative of NAEC, the Economics Department and the Statistics and Data Directorate).

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NEW ANALYTICAL TOOLS AND TECHNIQUES TO BETTER UNDERSTAND SYSTEMS

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1. The need for new tools and techniques

The world economy is a system where heterogeneous, global production networks (50 million firms with billions of physical links) interact with household networks (2 billion households, 3.3 billion workers and trillions of links to consumed products), a web of contracts (trillions), and ownership patterns where a few firms and individuals own almost everything. The economic system is inherently intricate and interlinked and offers complex interactions at the individual level that give rise to emergent properties at the macro level. Policymakers need new tools to understand this system, and while 50,000 person years have gone into researching the traditional tools and techniques, only approximately 500 person years have gone into researching agent-based models.

Understanding of economic issues such as growth, financial crises, systemic risk, innovation and sustainability can benefit from the revolution taking place across mathematics, the natural and social sciences. This revolution is being driven by the interaction of technological progress in computing and greater quantities of available data. Techniques drawn from disciplines such as mathematics and computer science have the potential to offer an in-depth analysis of the interactions within and across various networks and systems. These techniques include agent-based models, network models and big data analysis, which can bring to light how behaviours and properties emerge from intra- and inter-system interactions, including shocks in the financial, economic, social, and environmental systems. These new models will allow policymakers to better design policies, and assess not only the direct but also the multitude of indirect effects these policies may have.

While economists have frequently argued that their discipline has made considerable advances in recent years, it is clear that many policy-makers feel frustrated at what they see as efforts to improve abstract models without being of much practical help. In 2006, even before the 2008 crisis, Greg Mankiw who had just stepped down as the Chairman of the President's Council of Economic Advisers, said, “The fact that modern macroeconomic research is not widely used in practical policymaking is prima facie evidence that it is of little use for this purpose. The research may have been successful as a matter of science, but it has not contributed significantly to macroeconomic engineering”

What he meant by this is that one can think of science as providing the foundations for the tools which will then be put to use by the “engineers”. In Mankiw’s view, economic science has become too introverted and is not aiding practitioners to make use of their technical and theoretical advances. There are many reasons for this, most of which have to do with the sociology of the academic economics profession. But, unfortunately the gap has been most important in macroeconomics. Yet, the OECD is, of necessity, concerned with macro-economic policies.

The New Approaches to Economic Challenges (NAEC) Initiative has highlighted the need for a better understanding of complex, dynamic and interconnected challenges. NAEC is working closely with many leading institutions to develop these approaches. Notable institutions include the Santa Fe institute (USA), the Fields Institute (Canada), the International Institute for Applied Systems Analysis (IIASA) (Austria), and the Institute of New Economic Thinking (INET) at Oxford (UK) amongst others. In April 2018, NAEC organised the conference New Analytical Tools and Techniques for Economic Policymaking offering a timely opportunity for policymakers, academics and researchers in economics to discuss the state-of-the-art policy applications emerging from the new analytical tools and techniques. Recently, the Agent-based

Modelling (ABM) Lab at New York University and Google have also agreed to collaborate with NAEC on these issues. NAEC is facilitating the development, experimentation and exchange of these new techniques to provide the basis for better-informed policy advice. Furthermore, in November 2019, NAEC is organising a joint conference with Rebuilding Macroeconomics in London that will delve into the applications of complexity science in macroeconomics.

The NAEC group would not be pretentious enough to suggest that it can change the way the economics profession functions, but it does have an important role in providing the “engineers” with access to new ideas and techniques which are being developed, often outside academia (for instance in Central Banks and Government departments). The links that have been built by NAEC have turned into a network of expertise which can both help the OECD’s directorates in their quest to keep ahead of the game and develop policy recommendations which are both scientifically sound and practically implementable.

This note summarises the potential contributions of two promising approaches, which NAEC has focused on, namely ABM and machine learning. ABM is based on a bottom-up approach to understanding the economic system. In a large-scale simulation, agents are endowed with behavioural traits and macroeconomic phenomena are emergent properties of agent interactions. Machine learning has the potential to develop economic analysis through a less restrictive analysis of data, and development of richer non-linear relationships and interactions between effects. This can aid in forecasting, exposing the interlinkages in data, and understanding policy interactions. The note concludes with an update on the development of the NAEC Innovation LAB.

2. Agent-based Modelling

Agent-based modelling offers a ground-up approach to modelling economic systems. The idea of using an agent-based model (ABM) has been around since the idea of a von Neumann machine and Conway’s game of life. Since then, the modelling framework has progressed in intricacy and resemblance to empirically observed phenomena. One of the reasons for this increased growth has been the improvements in computational power that allow such large-scale simulations to be run. The basic idea is for the researcher to model individual agents and simulate their interactions at scale in order to derive insights. The benefits of such a representation are its ability to represent complex systems, emergent phenomena, endogenous shocks and non-linear dynamics. In this section, an overview of a typical ABM is given and the benefits of such an approach are discussed. This is followed by some examples of developed ABMs and further avenues for development in the field.

Models that take an agent-based approach are built around the individual classes of agents. These agents are endowed with behavioural heuristics that govern their interactions with other agents. Behavioural heuristics can be modelled on a variety of insights from psychology and behavioural economics, and the intricacy of the behavioural model is dependent on its purpose. For instance, the works of Kahneman, Tversky and Thaler can provide a basis for the behavioural models of agents. More importantly, this ground-up approach offers economists the opportunity for interdisciplinary engagement with the fields of psychology, sociology and anthropology to create an accurate representation of the intricacy of human behaviour.

One of the pre-eminent scholars in the area is Joshua Epstein, a NAEC partner, whose work entitled Agent Zero lays the foundations for the endowment of agents with distinct behavioural modules. It should be highlighted that such a ground-up approach avoids requiring an agent to be fully rational or have access to all information, an assumption frequently made in traditional economic models in order to make them solvable mathematically. These agents will then interact in an environment specified by the modeller. This can be a fixed network of interactions or a random process, and might include rules of learning and adaptation. The complexity of the economic system that these agents constitute then emerges as the simulation is run. In this regard, there is no central control enforced upon the model but rather the economic process, and macroeconomic properties, emerge through the interactions of individual agents. A simple ABM is the original Sugarscape model crated by Epstein and Axtell. In this simple example, the emergent properties consisted of the changes in wealth distribution. In the more modern models of the economy, there is a large plethora of emergent properties including observations such as endogenous crises and an endogenously created business cycle.

The basis for this model is a large grid with two mountains of high sugar availability. In this simulation agents have only one objective, to maximise their sugar intake (i.e. intake is larger than metabolism). Each turn they consider their environment and move to the point nearest to them that has high sugar availability. While a simple premise, such a model already shows how the distribution of wealth shifts from an egalitarian start (few rich or poor and many middle class) to a skewed distribution in which there were a swath of very rich agents and very poor agents with only a sliver of middle class present. The skewed distribution is an emergent property of the system, a macro property that emerges from the collective micro behaviour of agents.

The mainstream economic counterpart to large-scale ABMs is the dynamic stochastic general equilibrium (DSGE) and computational general equilibrium (CGE) models that have emerged from the developments in neoclassical economics. ABMs present several benefits over these other integrated assessment frameworks.

- First is the modularity that ABMs offer. Due to the ground-up approach in modelling only behavioural heuristics and interactions, ABMs can more easily incorporate studies from economics and other disciplines. For instance, the study of particular types of product market interactions or product selections. The reason for this modularity is that an ABM is a simulation and hence must not be mathematically solvable.
- ABMs are superior in capturing non-linear dynamics. For instance, technological and information diffusion are typically non-linear processes. Due to the network nature of interactions in an ABM the non-linear diffusion of such information can be more easily captured and might even be an emerging phenomenon from the interactions within the model.
- Inherent uncertainty is another aspect in which ABMs can be considered superior. Many economic phenomena stem from fat-tailed distributions, where extreme events can be more likely. In the typical DSGE framework, an expectation is taken over this distribution. However, this may often lose information about the fat-tailed nature of the underlying distributions. ABMs on the other hand often do not require such expectations to be taken. Rather, through repeated runs of the simulation the effects of the fat-tailed distributions can be extorted.
- Lastly, ABMs are not required to return to an equilibrium outcome. One of the common ideas in neoclassical economics is that the economy is in an equilibrium and will occasionally be uprooted from this equilibrium by a shock. However, once this shock is processed, the economy will once again head to an equilibrium state. In an ABM, a state of equilibrium might be an outcome however it is by no means the only one. ABMs allow for a variety of scenarios to emerge, including a state of constant flux, prolonged crises and punctuated equilibria. Shifts between these different states can also arise endogenously from the model of the economy itself, rather than be limited to exogenous means as may be done with equilibrium models.

While there are many benefits to the use of agent-based models, they have not received the same attention as traditional economic models. In the estimate of Doyne Farmer, 500,000 person-hours have gone into the development of neoclassical models for economics, while only 500 have gone into the development of agent-based approaches. However, the development of these approaches has been stark, and up-to-date models continue being developed both within and outside of economics. Notable applications include biology (spread of epidemics, population dynamics, evolution, cognitive modelling), business and technology (organisational behaviour, supply chain optimisation, consumer behaviour, social networks) and economics (primarily integrated macroeconomic models and financial markets). Some of the larger macroeconomic models that have been developed include the EURACE model, which emerged from a project by the European Commission and is now at the University of Bielefeld.

Similarly, there are the Keynes-meets-Schumpeter model and the Lagom RegiO models. While describing the details of each model is beyond the scope of this paper, it should be noted that they have all been applied in the frame of policy evaluation. For instance, in the realm of fiscal policy it was found that that the only means for countries to catch up in terms of GDP was through technology focused fiscal policy, as opposed to demand stimulation. Likewise, financial regulation and crisis resolution were investigated, among other topics. The paper “Macroeconomic Agent-Based Models” by Dawid and Delli Gatti provides a more detailed overview of the policy potential for these varied models. In the realm of finance, agent-based methods and network structures have been primarily used in the analysis of financial risk networks as well as the formation and resolution of crises. One interesting application is the creation of artificial stock exchanges, most notably by the Santa Fe Institute who, through the works of LeBaron, Brian Arthur, Holland and Palmer, have worked on this since the early 1990s.

The use of agent-based models should be further developed. Despite the increasing computing power available today it is a challenge to run ABMs at a scale matching actual countries, let alone the world. This requires tens of millions of agents and millions of firms to be simulated. Advances in machine learning, such as the use of graphic-processing units to apply parallel processing, as well as computational architecture need to be further developed such that ABMs can generate more of the range of emergent phenomena witnessed in the economy.

A frequent critique is that ABMs are sensitive to starting values and the specific behaviours programmed into the agents. While true, this can be negated through a larger number of simulations to generate distributions across all possible initialization options. More important is that emergent properties, or macro properties, are often the result of very complicated causal chains across time and space. This makes it both hard to identify the non-linear dynamics and aggregation mechanisms that underlie important results. However, there is a rich distributional outcome space of inputs and resulting scenarios that can be used to determine the effectiveness of policy in guiding the economic system towards a desirable outcome. Devoting resources to the understanding of the causal chains can open up a rich source of knowledge for the implementation of better policies for better lives.

With the support of the Investment firm Baillie Gifford, the NAEC Unit, with the Economics Department, is leading a flagship project featuring the development of new approaches to macro-modelling.). OECD has the data and experience and can help to: 1.) calibrate such models and develop policy questions, 2.) engage Member governments, Finance Ministries and Central Banks in their development and application and 3.) provide legitimacy for their relevance and usefulness in policy which academics alone would not be able to deliver.

Such models could then be used as a basis to work with other models from climate change, energy, labour markets, the financial system etc. This joint initiative between NAEC and INET Oxford (and the broader Oxford Martin School) has great potential. The relevant OECD Directorates would work together and the OECD may set up advisory bodies as appropriate to involve Members and Committees to ensure that such methodologies diffuse through the networks and structures of OECD into Member governments and the practice of economic analysis and policy.

3. Machine Learning

Machine learning and artificial intelligence has been a dominant thread of research across academic disciplines in recent years. The idea of machine learning applied to the field of economics and policy holds a lot of promise. As the field of machine learning covers a wide area of applications and model implementations that are beyond the scope of this paper, here the focus will be on the applications and benefits that machine learning can present in the understanding of the economic system.

Machine learning was formally defined by Mitchell as follows: “A computer programme is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks T, as measured by P, improves with experience E”. While this is an operational definition, machine learning may more widely be perceived as the development of algorithms for prediction, classification, and or grouping of data. In this regard, there are two categories: supervised learning, where data contains inputs and desired outputs, but also unsupervised learning, where data contains only inputs. The distinction of these two different avenues is important, as unsupervised learning was previously only possible in limited capacities (such as principal component analysis). The availability of such tools will allow a much wider ability to understand the generation of the data we observe, which can yield new insights. Within both of these categories, there are a multitude of models and approaches, some of which hold benefits for economic understanding.

The debate about the benefits and issues of machine learning and artificial intelligence in society are a topic of hot debate. For the domain of economics, machine learning proposes to offer the following substantial benefits:

- **Improved predictive ability**. In traditional economic and statistical analysis, linear approximations to problems are a common approach. In the case of non-linear data, transformations are applied to linearize before estimating relationships. However, these approaches are inherently limited in the set of functions, only linear ones, that they can represent. Prior to the advent of deep learning, such non-linear relationships had to be derived by hand. Deep learning allows the machine to learn, through data, the detailed non-linear dynamics of the underlying process, and thus predict outcomes with more accuracy. The reason for this is that neural networks are universal function approximations. Advances in these techniques have improved accuracy in both predictive scenarios as well as classification problems. Applications to forecasting financial time series have also been explored widely. Some key areas to explore might include long short-term memory (LSTM) models, recurrent neural networks or reservoir computing (chaotic time series) for their abilities in time-series analysis. These are particularly salient tools as they can incorporate data at different frequencies across time.
- **Unlocking vastly larger amounts of data**. Another aspect where advances in machine learning can advance the understanding of economic systems is the ability for deep learning tools to unlock larger amounts of data. With advances in areas such as image recognition, machine translation and speech recognition, more data is becoming available to researchers in economics. For instance, the evaluation of sentiment in financial and consumer markets has been augmented through natural language processing techniques that analyse news sources. Additionally, the amount of data on social networks and a variety of texts that was previously not usable in a quantitative manner has become accessible through deep learning processing methods. This has the potential to foster a richer understanding of the interactions and characteristics of the wide variety of economic agents, and hence improve an understanding of the economic system and the risks it faces.
- **Better understanding of data representations**. The models performing unsupervised learning promote a better understanding of the representations of existing data. For example, auto-encoders are a type of artificial neural network that learns the representation of data in order to reduce noise and reduce dimensionality. The use of deep learning here allows for the extraction of various hidden relationships in the data.

While machine learning offers a wide array of benefits, it is often difficult to implement without domain expertise. In this area, NAEC can facilitate connections with leading experts. Another issue in the development of machine learning tools for the purpose of policymaking is interpretability. Due to the complicated nature of the data generating processes that one of the neural network types can represent, as well as the large amount of input, it is often difficult to gain an intuitive understanding of the causal chain that is represented. However, building expertise in such a domain coupled with the policy expertise of the OECD has the potential to provide a much more accurate perspective of the economic system as well as predictions as to its development.

4. Neuroeconomics

A rapidly expanding field is that of the use of findings from the neurosciences in economics. It might seem paradoxical that the NAEC programme which puts so much emphasis on the interaction between individuals and which suggests that we have paid too much attention to dissecting and rationalising individual behaviour should also devote attention to opening up the “black box” of the human brain. Yet as Camerer and his co-authors have pointed out the rationality and consistency that we attribute to individual agents permeates the whole of economic theory and has been enthusiastically adopted by macro-economists who refer to this as “sound micro-foundations”.

Why then should we spend our time and energy on this approach? There are several reasons. Firstly, the rationality assumed by economists has regularly been observed to be violated in experiments and since, at least Pareto, the underlying axioms have been questioned. A first reaction and one which consists in modifying standard theory to take account of this problem is to suggest that humans are subject to biases which prevent them from behaving fully rationally. Such biases can be recognised and even corrected and reconciliation with the theory can be achieved in this way. But while this calls on part of the neurosciences and has become popular through the “nudge” approach it does not abandon the standard view of how humans function.

A more radical approach is to argue that human behaviour is much more complex than simple optimisation and calculation might suggest. Combinations, of the ingrained and evolutionarily developed mechanisms which govern many of our responses to situations and the reasoned calculations emanating from the prefrontal cortex together produce the behaviour which we observe. This coupled with the importance of the influence of emotions on behaviour makes it unreasonable to reduce human behaviour to simple optimisation problems.

But, this suggests that there is a fundamental problem with viewing economic activity both at the macro and micro level as the result of careful and sophisticated calculation. Thus, the basic model that we use to justify our analysis of economic and social behaviour may be fatally flawed. Understanding, the ways in which humans react to their environment both economic and social requires a revision of our basic axioms. If we are to build reasonable ABMs, for example, we should predicate the rules which we attribute to individuals on a basis which is consistent with our knowledge, however imperfect, of the neural mechanisms which govern choices.

But, there is another fundamental reason for being interested in the brain. Its structure and the way in which its decisions emerge from the interaction between individual neurons may give us deeper insights into how the economy functions. As Bob Shiller the Nobel Laureate, and an invitee of the NAEC programme said,

> *“An economy is a remarkably complex structure. The analogy between the brain and the computer is familiar but one can make the same analogy between the computer and the economy, a network of people who communicate with each other via electronic and other connections. Using our better understanding of the brain and the computer may help us to better understand the economy”.*

With this in mind, NAEC has organised a conference to which some of the leading authorities on neuroeconomics contributed, a further conference with the NEUREX European research consortium and is pursuing further interaction with neuroscientists both in the consortium and with the group at the University of Strasbourg and the Neurospin laboratory at Paris Saclay.

5. The NAEC Innovation LAB

The NAEC Innovation LAB was created to provide a space for researchers across the OECD to work together on specific projects that apply and experiment with new analytical tools and techniques. This will allow the OECD to strengthen and diversify its analytical tools and insights. Some Directorates have already begun undertaking smaller scale projects exploring new tools and techniques. These projects may carry greater risks than relying on existing techniques, but potentially offer high returns. Investigation and experimentation on a relatively small scale and in a safe environment may encourage required experimentation, while working with others will help diffuse lessons from experiences gained. As a platform for collaboration with wider communities, the LAB can foster links to make use of expertise and data from outside of the OECD.

Ongoing projects concentrate in four key areas: machine learning, big data, agent-based modelling and other experimental approaches. In the scope of agent-based modelling there is an exploration of financial interactions and network effects in the global economy. In the wake of the 2008 financial crisis, it is important to understand financial networks and the resilience of the financial system.

Machine learning techniques are currently being developed to enhance short-term macroeconomic forecasting and understand the non-linear interactions between growth-enhancing policies and inclusive growth outcomes. This opens up means to present model-based policy advice that is more country specific. Meanwhile, big data approaches have been used to understand the effect of technological change, trade and global value chains on prices and these implications for well-being.

In addition to existing initiatives within the OECD, the LAB has begun organising events such as workshops on agent-based modelling in labour markets and financial markets, machine learning and forecasting and introductions to machine learning. A physical space will open in November 2019 at the Boulogne Building of the OECD and NAEC has recently advertised a post for a Research Scientist to advance multi-disciplinary approaches to economics.

Current projects of the NAEC Innovation LAB include:

- Using agent-based modelling (ABM) to analyse financial interactions and network effects in the global economy based on a stylised representation of the financial system and the behaviour of key agents. This would highlight policy spill-overs and show how policies and institutions affect resilience.
- Using machine-learning techniques to improve short-term macroeconomic nowcasting/forecasting, and to understand the non-linear interactions between growth-enhancing policies and inclusive growth outcomes, allowing for rich interactions between policies and with country circumstances. This opens the way to give model-based policy advice that is more country specific.
- Using big data approaches to understand how prices are being affected by technological change and exposure through trade and global value chains with implications for well-being and policy.