Empirical Post Keynesian Research Methods

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Abstract

In recent years, few Post Keynesian economists have undertaken empirical research. Further still, discussions concerning empirical techniques are becoming increasingly scarce. There are many new and interesting developments in statistics that are rarely discussed among Post Keynesians. This paper is intended to encourage discussion among Post Keynesians regarding which, if any, of the new empirical tools presently in development may help further economic knowledge. Presented here are techniques such as spatial econometrics, econophysics, survival analysis, bioinformatics, artificial intelligence, and quantum mechanics; each of which provides a potential platform for Post Keynesian economists to differentiate their empirical research perspective and theories from the mainstream. Mainstream economists place high value on utilizing empirical tools, but they are typically slow to pickup on new statistical developments. Not all economic research requires using statistical methods, but much does, and ignoring recent fruitful developments in statistics is shortsighted. If Post Keynesians continue evading empirical testing, then many of their insights will lose weight and their position will deteriorate within the discipline of economics, generally.

Key words: artificial intelligence, bioinformatics, econophysics, empirical analysis, neural networks, parastatistics, pleiotropy, polygenics, Post Keynesian, spatial econometrics, survival analysis, system dynamics.

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This paper is an attempt to get more Post Keynesian economists engaged in discussions regarding innovative statistical techniques.[2] Many of the new statistical techniques in development currently are more aligned with Post Keynesian principles such as non-ergodicity and asymmetric information. Due to an increasing complexity of computer hardware and software, statistical techniques are in turn becoming more sophisticated and are thus gaining the ability to model ever more complex systems. In addition, statistical software has become more user-friendly, making once complicated statistical procedures, easy to perform. However, too few Post Keynesian economists are taking advantage of new empirical tools and techniques available today. Debates over methodology seem to be taking away from the potential fruitfulness of Post Keynesian empirical research, and away from tradition.

In this paper two broad topics concerning practical empirical research are covered. First, it is important for economists to be good empiricists. Econometric analysis, when performed properly, can produce useful results, and this process begins with good data collection. Second, there are numerous new and interesting statistical tools and techniques being developed. Many of these breakthroughs in statistical analysis are coming from hard science disciplines. Economists can use these new techniques to create better more accurate models with which to analyze economic issues. These are exciting times for statistical theory. And Post Keynesian economists need to recognize and embrace these changes and developments. These new techniques will help Post

[2] It should be stated here that there are several Post Keynesian who regularly engage in empirical work: Fred Lee, Michael Radzicki, Steve Pressman, James Galbraith, Paul Downward, J. Barkley Rosser, and even Paul Davidson, whose first discipline of study was biochemical engineering, and is seemingly not against the idea of more good Post Keynesian empirical analyses. In addition, Ric Holt and Steve Pressman have recently edited a book *Empirical Implications of Post Keynesian Economics* (2006) that showcases empirical work by Post Keynesians. However, these researchers are still an exception.

Keynesians legitimize their theories by giving further evidence that they are superior to all alternatives.

Data collection

The most important part of any empirical analysis is data collection. The quality of any study analysis is directly related to the quality of the data used. No matter how brilliant a model, theory, or techniques used, if data is of poor quality the results produced using it will be too. Therefore, economists should be deeply, obsessively concerned about obtaining data that meets high standards of excellence. The process of collecting data can be onerous. But it can also be liberating, and a way for Post Keynesians to differentiate themselves from other economists. Too many economists rely on secondary data sources such as government datasets. Sometimes collecting data is illegal or impractical; therefore, secondary sources are the only option. However, Post Keynesians should try to set a precedent that they rely mostly on data collected themselves.[3] In the hard sciences, researchers rarely (if ever) use secondary data. There are many reasons for this, such as (a) it is impossible to completely trust the quality and accuracy of data collected by someone else, and (b) when developing a survey questionnaire, one already has in mind what she wants to get from it; so, she has structured the questions so that responses are as accurate as possible given her research agenda.

Becoming encapsulated in the data collection process is a fascinating aspect of research, and is not terribly difficult. It is usually not necessary to collect tens of thousands of observations, such as is commonly done at the government level or when

[3] This is similar to grounded theory, but less stringent in structure.

large grants are awarded.[4] Usually, a researcher is looking to study one specific issue, so, developing a questionnaire of three dozen questions will often suffice.

Practical empirical work examples

The Oxford Economists' Research Group (OERG) epitomizes practical statistical analysis. The OERG was formed in 1936 by Roy Harrod and Hubert Henderson, and included over a dozen other Oxford scholars. OERG's purpose was to investigate "…the influences determining the trend of economic activity in Great Britain since 1924" (Lee, 1998, p. 85). Specifically, the OERG wanted to analyze the reasons behind businessmen's decisions. OERG's object-of-study was the economy, and they believed that analyzing businesses from the top-down gave them insight into the economy's mysteries.

But more interesting than the topics studied by OERG was the method they used for analysis. Instead of guessing what businessmen thought, they went to the source and invited businessmen to meet with them where they could analyze, first-hand, the processes and factors leading to businessmen's decisions. Sometimes members of the group met with businessmen at their business; and other times, OERG would invite businessmen to Oxford for food and libations creating a relaxed interviewing environment. This technique generated valuable results: for example, they found that none of the businessmen stated that interest rates influenced their investment decisions—a concept still widely misunderstood (Lee, 1998, p. 88). OERG's methodology was

[4] Usually government datasets are trying to serve a variety of researchers' needs, so they tend to be lengthy questionnaires. For example, the most recent US Survey of Consumer Finances (SCF) contains thousands of variables and over twenty thousand observations.

simple; however, too few economists take the time, effort, and care to engage in equally conscientious research. The essence of the OERG should be modeled and assimilated into present Post Keynesian empirical research.

Card and Kruger's (1994) analysis of minimum wage and employment rates is an example of solid empirical economic research. Their paper was published in the *American Economic Review*, but could have just as easily been published in the *Journal of Post Keynesian Economics*. They performed their study using the fast food industry when New Jersey issued a state wide increase in the minimum wage rate. They compared the effects of New Jersey's (experimental group) newly increased wage rates to the unchanging wage rates of its neighboring state Pennsylvania (control group). Using a questionnaire they developed, they analyzed the various effects of New Jersey's new minimum wage rate. They used telephone survey methods to collect their data.

Their results showed that an increase in the minimum wage rate, contrary to neoclassical theory, did not increase unemployment, but rather reduced it. This increase in minimum wage workers' wages also caused a "ripple effect" that resulted in higher wages for non-minimum wage workers. Furthermore, their analysis showed that few teens were utilized in the fast food industry, and that companies did not reduce benefits to compensate for an increase in wages. Again, Card and Krueger's findings are converse to neoclassical theory. Their empirical results are simple and straightforward. Arguably, any Post Keynesian economist could have performed the same study as Card and Krueger; but, it is argued in this paper, too few Post Keynesian economists are thinking empirically, so they do not consider projects such as the one performed by Card and Krueger, and herein lies our problem of econometric negation.

Data analysis

Econometrics should help economists explain the economic system and further their understanding of it. Econometrics is designed to clarify, not predict with certainty. At best econometrics provides some insight into what has happened in the past and what is occurring currently. But it can also help to identify social tendencies and outcomes that translate into future events, but maintain the concept of non-ergodicity. Truly, econometrics today can, in fact, show directional tendencies of the economy and society by using some of the newer statistical techniques available. For example, it is possible to predict using spatial econometrics (discussed below) what areas in a region are at greatest risk for environmental degradation, and then develop and implement appropriate policies. Prediction will never be perfect, but it does not have to be. Econometrics simply has to show a tendency toward a certain direction in certain areas and then help researchers determine how extensive the damage might be. Using econometrics in this way is extremely useful and powerful (Davidson, 1996).

A misunderstanding exists in the minds of many of econometrics' opponents because they often conflate descriptive statistics with inferential statistics into the term econometrics. But they are actually two different things; thus, econometrics should be separated into descriptive econometrics and inferential econometrics (or, inductive econometrics and deductive econometrics, respectively). In other words, one can perform an econometric analysis using purely descriptive tools and develop conclusions and predictions just as resolutely using these tools as they would using inferential ones.

Economists are now beginning to understand the value of data mining (DM) (or, exploratory data analysis). Too many empiricists, however, still view DM as a sinful, unethical concept. But this is false. In fact, DM is, in principle, a Post Keynesian value because it emphasizes investigation and uncertainty while nearly eliminating the idea of perfect foresight. By performing DM a researcher claims ignorance concerning what variables are going to influence the dependent variable; or, that they do not know which statistical technique will work best, but through exhaustive trial and error the answers will slowly emerge. Uncertainty is not only acceptable in empirical research, it is natural.

It is simple-minded to think one can develop a theory, test it using un-mined data, and expect to get statistically significant results the first time, such as is commonly done today. If one does get statistically significant results from this approach it is probably by accident, hence why many empirical results fall under suspicion; and, this technique compels some people to carry out unethical practices, such as data manipulation. DM eliminates these concerns, it provides freedom to take a dataset and try new and different things without fear of wrongdoing. Post Keynesians need to support this kind of analytical strategy to eliminate concerns about getting insignificant results. So, henceforth for Post Keynesians data mining is a dysphemism.

Developments in econometrics: past, present, and future

Many of the techniques used in econometrics today spawned from work in the hard sciences. For example, models that analyze categorical and multivariate loglinear logistic models (logit and probit) were developed in the field of biometrics. Few of the statistical techniques discussed below have been used by Post Keynesians. But many of the newer statistical techniques appear theoretically inline with Post Keynesian philosophy; i.e. they embrace uncertainty, question strict traditional econometric assumptions, discard equilibrium conditions, and acknowledge time as a factor of influence in models. Therefore, Post Keynesians should engage in discussions about what new techniques are purposeful to them and which are not. This paper should serve merely as a beginning to these discussions. And, if Post Keynesians deem new statistical techniques invalid/valid or inappropriate/appropriate, then at least literature is available that clearly specifies Post Keynesians' disagreements/agreements with the techniques. Simply stating that econometrics is ineffective is inadequate, because statistics, like everything, is not neutral; and as a result, it is necessary for Post Keynesians to regularly debate newly developed statistical techniques so that if/when a useful technique(s) comes along economists will be well positioned to defend their disuse/use of it.

Spatial econometrics

The invention of geographic information system (GIS) computer software created a powerful new platform to integrate, store, display, and analyze geographically-referenced information. It was nuclear weapon research in the early 1960s that facilitated the invention of dedicated software specifically designed for complex geographical mapping. The first fully functional GIS system was created by Roger Tomlinson for Canada's Department of Energy, Mines, and Resources (DEMR), so Tomlinson called his invention the Canadian GIS (CGIS). The DEMR used CGIS to study information such as animal migration, soil, recreation, forestry, and so forth. While mapping has existed in many forms for thousands of year, what made CGIS innovative was its ability to measure and overlay reference data with strict geographical data. For example, the DEMR could see what areas in rural Canada were experiencing droughts. They could study the severity of the drought, and more importantly analyze causes, such as seasonal effects or changes in weather patterns in general. This information proved valuable to DEMR when they wanted to determine what issues needed their attention most. CGIS also allowed researchers to scan/input information easily into the program, which made large scale data collection convenient. CGIS was the industry standard until the 1990s, but it was never available commercially; although, components of CGIS's basic architecture algorithms are still used in GIS programs today.

CGIS's success created a market for commercially available GIS programs, for which there are many, but the world leader is ESRI (Environmental Systems Research Institute).[5] ESRI started developing GIS software in the late 1960s. They produce many pieces of software that enhances users' GIS coded data management and analysis. However, their latest desktop based GIS software package is ArcGIS version 9.1, which lets users visualize, analyze, create, and manage geocoded data.[6] Their software is used by academics, small businesses, large businesses, and governments the world over. Most importantly ArcGIS lets researchers overlay different types of information for complex analysis of correlation, patterns, and/or clustering. ArcGIS lets one identify school districts, types/frequency of crime, and even individual housing units or plots of land to study a variety of issues. For instance, if someone believes that house prices are

[5] There are several GIS programs available for commercial use from other companies: Oracle, GE Energy, and Intergraph just to name a few. However, ESRI produced what is generally considered the world standard in GIS software technology.

[6] ArcGIS is a suite of integrated software packages including ArcView, ArcEditor, ArcInfo, and ArcReader (free). And additional add-on software is available for specific needs, such as business, military, and aeronautics.

increasing more in one area of the US (or, state, county, city, neighborhood, or even block) versus another, they can easily get housing price data and the location of the houses to produce a geographical representation of where the high housing prices are principally located. Researchers can take this example to a much more complex level; in other words, someone can look at why housing prices are high in those areas and get data about the quality of the school districts, crime rates, and racial ethnicity ratios to see if these factors might be correlated with high house prices (we get to the inferential implications below) (Morisaki and Nishi, 2001).

The real value of GIS for economists is that it gives them the freedom to not only view actual changes in social environments, such as housing prices, urban sprawl, and migration, but it also lets them view physical environments such as rivers, lakes, and estuaries to assess their quality and stability to see if they are decreasing/increasing over time and what the possible causes might be. So, from a purely descriptive econometric analysis perspective, GIS is inimitably valuable for economists because they can observe patterns in data geographically; i.e. in space (locations, densities, distances), which was impossible to analyze effectively before the widespread development of sophisticated computers.

Spatial econometrics was shaped from the fact that when data has a locational component two problems surface: (a) observations are dependent upon one another spatially, and (b) spatial heterogeneity arises during model specification. These two problems violate Gauss-Markov assumptions—a fact conveniently ignored by many econometricians. Until the recent developments in spatial econometrics, econometricians had completely ignored the impact of space on their models. Early research in the field of spatial econometrics (Lebart, 1969; Paelinck, 1975; Thompson and Mattila, 1959) raised concerns about problems concerning accuracy of contemporary models that ignored spatially influenced variables—and it is still largely ignored (Wong and Lee, 2005).[7]

Spatial econometrics is still developing; regardless, too few economists are using it, and very few (if any) Post Keynesians. It offers a distinct opportunity for Post Keynesians to employ a heretofore under-utilized tool and stake a claim in its usefulness for economic research, thus further promulgating practical Post Keynesian empirical analysis. Furthermore—if it makes readers feel better—there is no mention of spatial data, models, or theory in any of the bestselling contemporary econometric textbooks.

Econophysics

Economics and physics have a, roughly, one hundred year relationship with one another, probably dating back to Einstein's work on Brownian motion. The contemporary term used to define the intermingling between economics and physics is econophysics, which according to Bikas Chakrabarti (2005) was first used by H. Eugene Stanley at a Statphys (statistics/physics) conference in Kolkata in 1995. Due to the increasing number of physicists working in the field of finance, it was only a matter of time before a sub-field developed. When physicists first started working on finance problems, they found traditional economic models inadequate to explain and predict events they were observing in financial markets. Specifically, econophysics theorists have found that

[7] Analyzing geocoded data inferentially requires additional software not available in ArcGIS; although ESRI does have GIS statistical software available (ArcGIS Geostatistical Analyst ($2,500)). For most researchers, SAS offers the most options and greatest flexibility for analyzing geocoded data. Current versions of SAS are ArcGIS-friendly allowing for easy importing/exporting of data and analysis.

financial data does not obey normal/Guassian, distributions.[8] Financial data regularly has fatter and/or longer tails than is observable in pure normal distributions. Consequently, their investigations have led to better explanations of the distributions of financial data. They have adopted non-linear models that account for observations with uneven stochastic errors that are often discovered in financial data (Boyarchenko and Levendorskii, 2002). In other words, econophysicists are trying to develop models that more precisely take into account the erratic behavior of variables influenced by unpredictable random performance (Brooks, 2002; Cerny, 2003).

Fischer Black and Myron Scholes (1973) set into motion the development of econophysics with their design of an option pricing model that eventually led to the Black-Scholes-Merton (BSM) partial differential equation that has become an industry standard in the field of finance (taking various forms throughout time)—mostly because its non-linearity better explains financial market flux. Interestingly, BSM is simply a transformation of physics' heat partial differential equation, which is used to study temperature changes in a homogeneous region over time. A detailed description of this transformation is found in Paul Wilmott, Jeff Dewynne, and Sam Howison's book *Option Pricing: Mathematical Models and Computation* (1994); see also John Hull's now classic sixth edition text *Options, Futures and other Derivatives* (2005).

Econophysics is just now emerging into a field of serious research. Its applicability is being demonstrated everyday by finance firms worldwide. However, whether it has lasting influence is debatable. But Post Keynesians should make their

[8] Abraham de Moivre in 1734 was the first known person to use a normal distribution formally—roughly, 50 years before Gauss claimed discovery.

opinions known on this topic, especially since it is starting to play a more critical role in market decisions.

Survival analysis

Economists often use longitudinal event data; and with such data economists encounter two difficulties (a) almost all samples have some *censoring*; i.e. the sample contains observations that do not experience the event under investigation, and (b) most economic variables change over time—time dependent (income, debt default risk, level of education). However, traditional regression analysis is impotent to test sample data that contains either censoring or time dependent covariates. Survival analysis (also known as duration analysis or reliability theory), however, resolves the difficulties associated with the two problems above (Hosmer and Lemeshow, 1999; Klein and Moeschberger, 2005).

Survival analysis was first developed by biostatisticians to study treatment time relative to time of death (realization of the event). However, in economics an example would be to study an event such as bank failure and analyze the potential influences leading to banks' failures over time. The example need not be so extreme—instead one could look at college dropout rates or when the US stock market loses more than 5 percent of its value in a day; in other words, a defined event's death need not be an infinite completion, but rather a mathematical signal that something has changed.

Survival analysis is used by mainstream economists currently. But because it takes into consideration the influence of time on variables' behavior (a tenet of Post Keyensianism) it is a more practical tool for Post Keynesians versus basic linear regression analysis. Therefore, survival analysis' usefulness deserves investigation as a functional method for theory investigation, justification, and discovery.

Bioinformatics: genomics: polygenics and pleiotropy

The term bioinformatics is not well defined, but generally, informatics is the creation, development, and operation of databases and other computing tools to collect, organize, and interpret data (Collins, Patrinos, Chakravarti, Gesteland, and Walters, 1997). Therefore, bioinformatics is simply informatics applied to biological science; i.e. it encompasses all new statistical techniques developed, such as those that deal with issues in genomics and computational biology (Sen, 2001). Some readers may wonder what biology has to do with Post Keynesian economics (or economics, in general), but it is surprisingly useful. Take, for instance, the cellular laws of vital activity that state: "living cells are never at rest, they are either discharging energy or renewing it […] cells exhibit their peculiar function […] and at the same time discharge an impulse, which exerts an influence on neighboring cells" (Kelly, 1960, p. 179). Therefore, statistical methods used in biological sciences are more adept at managing stochastic entities/environments that are often observed in economic data.

The field of genomics began with the discovery of deoxyribose nucleic acid's (DNA's) structure the double-helix by James Watson and Francis Crick in 1953 (Watson, 1969). Their breakthrough led technology through a time of ever increasing advancements in biology and chemistry. The Human Genome Project (HGP) was completed in 2003 and may eventually be remembered as one of the single greatest achievements of humankind. HGP served a number of purposes: first, it identified over

20,000 genes in human DNA; second, it "determine[d] the sequences of over three billion chemical base pairs that make up human DNA." Analysis of data after HGP was complete is ongoing and will continue indefinitely (www.genome.gov). The potential practical implications of genome mapping research are overwhelming. This research may lead to the elimination of all human genetic defects, diseases, and so forth.

According to Minoru Kanehisa and Peer Bork (2003) bioinformatics has advanced greatly because of HGP: "Sequenced based methods of analyzing individual genes or proteins have been elaborated and expanded, and methods have been developed for analyzing large numbers of genes or proteins simultaneously, such as in the identification of clusters of related genes and networks of interacting proteins" (p. 305). Besides strict analytical advancements, HGP has reinvented large dataset management. HGP developed new database programs to handle the kinds of data they were collecting and analyzing. These advancements will be beneficial to all disciplines that are using ever larger datasets.

Another valuable contribution of genomics is better gene clustering models, which are necessary for identifying patterns among genes in time and space. Conventional cluster analysis techniques proved insufficient for gene mapping; so, genomics has developed new techniques (for example, the *gap statistic* and *clest procedure*) that allow for more thorough and complex cluster analysis (Tibshirani, Walther, Botstein, and Brown, 2001; Fridlyand and Dudoit, 2001). There are many applications of cluster analysis in economics, particularly as a descriptive tool: for instance, analyzing clusters of (a) quality education availability/access; (b) racial demographics; and (c) health care services. There are many uses for these new statistical models. And, perhaps most important, if one is using a sophisticated inter-disciplinary statistical software package such as SAS, they can use computational biology processes and macros that are already available to run econometric cluster analysis.

In genomics there are two important concepts (a) polygenics, and (b) pleiotropy. The first concerns the influence of inheritance patterns of a trait caused by multiple genes' influence (Pilarski, Mehta, Caulfield, Kaler, and Backhouse, 2004). The latter term is the analysis of the mechanism by which one gene's change influences other genes (phenotypic traits) (Dudley, Janse, Tanay, Shamir, and Church, 2005). Genomics is directly involved in constructing ways to handle this amalgam of genetic interactions. Again, these tools may one day prove useful for studying economic systems.

Neural networks and system dynamics

The first artificial neuron was created by neurophysiologist Warren McCulloch and logician Walter Pitts in 1943. Their paper modeled the behavior of a basic artificial neuron.[9] The model had multiple inputs resulting in a single output—either 0 where the neuron remained inactive; or 1 it was activated. This research marked the beginning of neural network science (MucCulloch and Pitts, 1943). In 1959, Frank Rosenblatt developed the first neural network using a concept he called *perceptron*. The output (perceptron) produced fluctuates between 1 and -1 given inclusion of weighted linear inputs. Using perceptrons, he organized a simple single-layer artificial neural network (Rosenblatt, 1959). But because perceptrons could not account for multiple layers of

[9] An artificial neural network is, typically, a software program designed to have like a neural network; however, neural networks are usually hardware designed specifically to assimilate neural networks.

information they have since been discarded or modified to behave more like human neural networks.

Presently, there are two neural network approaches being researched that account for networks' nonlinear nature: (a) multilayered feed-forward networks (MFFN), and (b) symmetric recurrent networks (SRN). It is commonly believed that a neural network is not strictly a statistical method; i.e. they do not behave in the same way as traditional statistical models. One reason for this is that once neural networks are trained they grow according to the information fed to them, but the inner-workings of the model change each time new information is driven into the model, so the inner processing is unobservable. Because of neural networks mysterious procedure we cannot think of them as statistical because statistical models algorithms are well defined (observable). However, neural networks are capable of producing statistical results (probabilities, estimations, etc.), but the underlying methods by which the program uses to get its results will forever remain hidden. Depending on one's research purposes, this idiosyncrasy is potentially irrelevant (Yoon, Swales, and Margavio, 1993).

What makes neural networks interesting are their characteristics: (a) adaptive learning (associative mapping): they can perform tasks by learning from incomplete data and change its cognitive approach accordingly; (b) self-organization: they manipulate and present/store results uniquely; (c) real-time processing: computations are made in parallel; and (d) load balancing: damage to part of the network does not necessarily bring the entire network down, but rather a partial network can still function until the damaged portion is fixed. Neural networks are interesting because they do not operate algorithmically (i.e. instructionally), but cognitively, which is similar to human thought patterns. Because neural networks are cognitive, they can solve problems in a nonlinear fashion making connections between seemingly unconnected pieces of information, which allows them the ability to produce unique heretofore incalculable results. In other words, they take on artificially intelligent thought processes via experiential knowledge.

System dynamics (SD) is another newly developing modeling technique. This field of research began when Jay Forrester published *Industrial Dynamics* (1961). SD takes into consideration causal relationships between variables. In the economy, for example, it is known that one set of events can have a causal impact on other events; and, furthermore, these causal events are probably part of a larger pattern of behavior in the system. The problem with identifying causal relationships between events, particularly groups of events, is that there may be a large number of factors influencing the event. For example, in the US economy, the factors that cause recessions are numerous and represent a mixed bag of issues, so addressing any one issue at a time will probably not result in fewer recessions. But system dynamics modeling avoids this type of problem by focusing not on the internal mechanizations of the system, but rather the system in general. In other words, SD looks for the lowest common denominator of a pattern of behavior and then models those factors. Whereas many research methods take a myopic view of a problem, SD analyzes a system's general structure; i.e. a macro view.

SD is based on a feedback loop. A feedback look is when part of the output of a model is sent back through the model as an input. For example, when one washes her hands she initially turns on the faucet(s). It is rare that the temperature is just right immediately, so sne usually has to wait for the temperature to equalize (either hot, or cold). Once the temperature stabilizes you make minute adjustments to the faucet(s) to reach your ideal hand washing temperature. Complex problems in an economy or natural environment rarely stabilize, so the model is continually adjusting and taking into account fluctuations produced from varying inputs and outputs. Therefore, SD is usually trying to capture movements, or patterns, that lead to a problem's solution. SD lets researchers implement and adjust inputs to measure their effect (or lack there of) on a problem or issue under investigation.

SD is a known system. Researchers create computer simulations that include equations/tables that account for patterns of behavior they are observing. And, as was explained above, neural networks have an unknown internal mechanism that provides unique results through experiential learning. So these are two different methods for analyzing complex problems in a nonlinear manner. But the two may be integrated when conditions arise. Due to complex systems chaotic, nonlinear nature, it is difficult, and sometimes impossible, to account for all causal inputs affecting a given outcome. So, when important system inputs are unable to be specified structurally in an SD model, one can use neural networks as proxy variables to account for any unknown inputs. This method may be particularly useful when studying economics issues, which are often chaotic, nonlinear, and difficult to model differentially.

Concluding remarks

In order for Post Keynesian economics to grow it will have to get involved in discussions concerning old, new, and future empirical analytical techniques. Discussions among Post Keynesians should include issues about statistical relevancy or simply statistical methodology, which are ongoing topics of discourse in other disciplines. This is not to suggest that Post Keynesians should become strictly empirically oriented, but it cannot take the opposite route either.

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