Neuroeconomics and Agent-Based Computational Economics

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ABSTRACT
Recently, the relation between neuroeconomics and agent-based computational economics (ACE) has become an issue concerning the agent-based economics community. Neuroeconomics can interest agent-based economists when they are inquiring for the foundation or the principle of the software-agent design. It has been shown in many studies that the design of software agents is non-trivial and can determine what will emerge from the bottom. Therefore, it has been quested for rather a period regarding whether we can sensibly design these software agents, including both the choice of software agent models, such as reinforcement learning, and the parameter setting associated with the chosen model, such as risk attitude. In this paper, we shall start a formal inquiry by focusing on examining the models and parameters used to build software agents.

Keywords: Agent-based computational economics, Neuroeconomics, Methodological individualism, Multi-agent system, Hyperbolic discounting, Dopaminergic reward prediction hypothesis, Dual system conjecture, Individual learning, Social learning, Modularity

1. NEUROECONOMICS: AN ACE VIEWPOINT

From the perspective of agent-based computational economics (ACE), our interest in neuroeconomics is different from that of general psychologists and neural scientists. Agent-based computational economics advocates a *bottom-up research paradigm* for economics. This paradigm does not treat micro and macro as two separate entities and work with each of them separately; instead, it studies the relationship between the two in a coherent framework. Therefore, given the bottom-up manner, we pay more attention to the micro details, and always start the modeling at the level of agents. This *methodological individualism* drives us to incorporate the psychological, cognitive, and neural attributes of human beings into the study of economics. What causes ACE to differ from these behavioral sciences is the scope of the research questions; therefore, while ACE cares about the fundamental cause (the neural cause) of the cognitive biases, it is more concerned with the implications of these cognitive biases for any possible emergent mesoscopic or macroscopic phenomena. Furthermore, ACE researchers do not regard the behavioral factors as given (exogenous); they also study the feedback from the aggregate level (social outcome) to the bottom level (individual behavior). [i]

Given what has been said above, we believe that unless neuroeconomics can provide some important lessons for agent-based computational economists, its significance may hardly go far beyond neural science, and would not draw much attention from economists. This, therefore, motivates us to ask: *Does neuroeconomics provide some important lessons for agent-based economic modeling*? It is this question that this paper would like to address.

In the following, we will review the recent progresses in neuroeconomics in light of its contributions to different aspects of agent engineering. We start from the most fundamental part of agents, i.e., preferences (Section 2), which points to two foundational issues in economics, namely, the *measurement* or *representation* of preference and the *formation* of preference. Some recent advances in the study of these two issues may lead to new insights in the future of agent engineering with regard to *preference development*. We then move to the immediate issue after preferences, i.e., *choices*, or, more precisely, value-based choices (Section 3), and further specify the *intertemporal choice* (Section 3.1), where we can see how the *discount rate* should be more carefully designed. We then focus more on two behavioral aspects pertaining to the design of financial agents, namely, *risk perception* (Section 3.2.1) and *risk preference* (Section 3.2.2). The neural mechanism regarding learning or adaptation is given in Section 4. Finally, the chapter ends with a final remark that connects the relationships among behavioral economics, neural economics and agent-based economics, which is a continuation of the points made earlier (Chen, 2008).

2. PREFERENCE

"The nature of wealth and value is explained by the consideration of an infinitely small amount of *pleasure* and *pain*, just as the theory of statics is made to rest upon the equality of indefinitely small amounts of energy. (Jevons, 1879, p. 44; *Italics*, added)"

Standard economic theory takes individual preferences as given and fixed over the course of the individual's lifetime. It would be hard to imagine how economic models can stand still by giving up preferences or utility functions. They serve as the very foundation of economics just as we quoted above from William Stanley Jevons (1835-1882). Without preference or utility, it will no longer be clear what we mean by welfare, and hence we make welfare-enhancing policy ill-defined. Nevertheless, preference is now in a troubling moment in the development of economics. Even though its existence has been questioned, the development of neuroeconomics may further deepen this turbulent situation.

2.1 The Brain as a Multi-Agent System

The recent progress in neural science provides economists with some foundational issues of economic theory. Some of its findings may lend support to many heated discussions which are unfortunately neglected by mainstream economics. The most important series of questions is that pertaining to *preference*. While its existence, formalization (construction), measurement, consistency and stability has long been discussed outside mainstream economics, particularly in the realm of behavioral economics, neuroeconomics provides us with solid ground to tackle these issues.[ii]

To see how neuroscience can inform economists, it is important to perceive that the *brain is a multi-agent system*. For example, consider the *Triune Brain Model* proposed by Maclean (1990). The brain is composed of three major parts: the reptilian brain (the brainstem), the mammalian brain (the limbic system), and the hominid brain (the cerebral cortex). Each of the three is associated with different cognitive functions, while receiving and processing different signals. The three parts also have various interactions (competition or cooperation) with the embedded network. The three "agents"' and their interactions, therefore, constitute the very basis of this multi-agent system.

This multi-agent system (MAS) approach to the brain compels us to think hard on what would be a *neural representation of preference*. Preference is unlikely to be represented by a signal neuron or a single part of the brain, but by an emergent phenomenon from the interactions of many agents. Hence, many agents of the brain can contribute to part of the representation. So, when asked what the preference for commodity *A* is and its relative comparison for *B*, many agents of the brain work together either in a synchronous or asynchronous manner to generate a representation, the utility of *A* and *B*, say *U(A)* and *U(B)*.

During the process, some agents retrieve the past experiences (memory) of consuming *A* and *B*, and some agents aggregate this information. These processes can be collaborative or competitive; it is likely that some agents inhibit other agents to function. As a result, the memory can be partial, which, depending on the external elicitation and other conditions, can vary from time to time. This rough but simple picture of the multi-agent neurodynamics may indicate why a steady preference conventionally assumed in economics may not be there. The alternative is that people do not have given unchanging preferences, but rather their preferences are constructed to fit the situations they face. Herbert Simon is one of the precursors of the idea of preference construction (Simon, 1955, 1956).

2.2 Preference Construction

"On the contrary, we approach choice within specific, quite *narrow frames of reference* that continually shift with the circumstances in which we find ourselves and with the thoughts that are evoked in our minds by these particular circumstances. Thus, in any given choice situation, we evoke and make use only a small part even of the limited information, knowledge and reasoning skills that we have stored in our memory, and these memory contents, even if fully evoked, would give us only a pale and highly inexact picture of the world in which we live." (Simon, 2005, p. 93, *Italics* added)

The MAS approach to the study of the brain may connect us to the literature on preference construction for real human beings (Fischhoff, 1991; Slovic, 1995; Lichtenstein and Slovic, 2006), and, in particular, the role of *experiences* and *imagination* in preference formation. In the following, we would like to exemplify a few psychological studies which shed light on the *experience-based* or *imagination-based* preferences.

Adaptive Decision Makers (Payne, Bettman, and Johnson, 1993) The *effort-accuracy* framework proposed by Payne, Bettman, and Johnson (1993) represents an attempt to shift the research agenda from demonstrations of irrationality in the form of heuristics and biases to an understanding of the causal mechanisms underlying the behavior. It has considerable merit as a model of how decision makers cope with cognitive limitations. The *adaptive decision maker* is a person whose repertoire of strategies may depend upon many factors, such as cognitive development, experience, and more formal training and education. Payne, Bettman, and Johnson (1993) suggest that decision-making behavior is a *highly contingent form* of information processing and is highly sensitive to task factors and context factors. They consider that the cognitive effort required to make a decision can be usefully measured in terms of the total number of basic information processes needed to solve a particular problem using a specific decision strategy. In addition, they state that individual differences in decision behavior may be related to differences in how much effort the various elementary information processes the individuals are required to make.

Hedonic Psychology Hedonic psychology is the study of what makes experiences and life pleasant or unpleasant (Kahneman, Diener, and Schwarz, 2003). It is concerned with feelings of pleasure and pain, of interest and boredom, of joy and sorrow, and of satisfaction and dissatisfaction. All decisions involve *predictions of future tastes or feelings*. Getting married involves a prediction of one's long-term feelings towards one's spouse; returning to school for an advanced degree involves predictions about how it will feel to be a student as well as predictions of long-term career preferences; buying a car involves a prediction of how it would feel to drive around in different cars. In each of these examples, the quality of the decision depends critically on the accuracy of the prediction; errors in predicting feelings are measured in units of divorce, dropout, career burnout and consumer dissatisfaction (Loewenstein and Schkade, 2003).

Empathy Gaps People are often incorrect about what determines happiness, leading to prediction errors. In particular, the well-known *empathy gaps*, i.e., the inability to imagine opposite feelings when experiencing heightened emotion, be it happy or sad, lead to errors in predicting both feelings and behavior (Loewenstein, 2005). So, people seem to think that if disaster strikes it will take longer to recover emotionally than it actually does. Conversely, if a happy event occurs, people overestimate how long they will emotionally benefit from it.

Psychological Immune System The cognitive bias above also indicates that agents may underestimate the proper function of their psychological immune systems. The psychological immune system is a system which helps fight off bad feelings that result from unpleasant situations (Kagan, 2006). This system is activated when humans are faced with potential or actual negative events in their life. The system functions to assist in protecting humans from extreme reactions to those negative events. Sharot, De Martino and Dolan (2008) studied how hedonic psychology affects our choices from a neural perspective. They combined participants' estimations of the pleasure they will derive from future events with fMRI data recorded *while they imagined those events*, both before, and after making choices. It was found that activity in the *caudate nucleus* predicted the choice agents made when forced to choose between two alternatives they had previously rated equally. Moreover, post choice the selected alternatives were valued more strongly than pre-choice, while discarded ones were valued less. This *post-choice preference change* was mirrored in the caudate nucleus response. The choice-sensitive preference observed above is similar to behavior driven by reinforcement learning.

3 VALUE AND CHOICE

“Neuroeconomics is a relatively new discipline that studies the computations that the brain carries out in order to make value-based decisions, as well as the neural implementation of those computations. It seeks to build a biologically sound theory of how humans make decisions that can be applied in both the natural and the social sciences.” (Rangel, Camerer, and Montague, 2008)

“In a choice situation, we usually look at a few alternatives, sometimes including a small number that we generate for the purpose but more often limiting ourselves to those that are already known and available. These alternatives are generated or evoked in response to specific goals or drives (i.e. specific components of the utility function), so that different alternatives are generated when we are hungry from when we are thirsty; when we are thinking about our science from when we are thinking about our children.” (Simon, 2005, p. 93)

The very basic economics starts with value assignment and choice making. However, traditional economics makes little effort to understand the cognitive and computation loading involved in this very fundamental economic activity. A number of recent studies have challenged the view that what we used to be taught may be misplaced when we take into account the value-assignment problem more seriously (Iyengar and Lepper, 2000; Schwartz, 2003). These studies lead us to question the impact of the dimensionality of choice space upon our behavior of value assignment and choice making. It seems that when the number of choices increases, the ability to make the best choice becomes problematic.

Going one step further, Louie, Grattan, and Glimcher (2011) attempt to theorize this paradox of choice by exploring the neural mechanism underlying value representation during decision-making and how such a mechanism influences choice behavior in the presence of alternative options. In their analysis, value assignment is relatively normalized when new alternatives are presented. The linear proportionate normalization is a simple example. Because value is relatively coded rather than absolutely coded, the value differences between two alternatives may become narrow when more alternatives are presented.

3.1 Intertemporal Choice

Agent-based economic models are dynamic. Time is an inevitable element, and the *time preference* becomes another important setting for agents in the agent-based models. However, in mainstream economic theory, the time preference has been largely standardized as an exponential discounting with a time-invariant discount rate. However, recent studies have found that people discount future outcomes more steeply when they have the opportunity for immediate gratification than when all outcomes occur in the future. This has led to the modification of the declining discount rates or *hyperbolic-discounting* (Laibson, 1997). Frederick, Loewenstein, and O'Donoghue (2002) provided an extensive survey on the empirical studies showing that the observed discount rates are not constant over time, but appear to decline.

Loewenstein (1988) has further demonstrated that discount rates can be dramatically affected by whether the change in delivery time of an outcome is framed as an *acceleration* or a *delay* from some temporal reference point. So, when asked whether they would be willing to wait for a month to receive \$110 instead of receiving \$100 today, most people choose \$100 today. By contrast, when asked whether they would prefer to speed up the receipt of \$110 in a month by receiving \$100 today instead, most people exhibit patience and take the \$110 in a month. This phenomenon has been used as evidence for the *gain-loss asymmetry* or the *prospect theory*. It has also been connected to the *endowment effect*, which predicts that people tend to value objects more highly after they come to feel that they own them (Kahneman, Knetsch and Thaler, 1990; Kahneman, 1991). The endowment effect explains the reluctance of people to part with assets that belong to their endowment. Nonetheless, Lerner, Small and Loewenstein (2004) show that the agents' *mood*, sad or neutral, can affect the appearance of this effect.

Query Theory Recently, query theory, proposed by Johnson, Haeubl and Keinan (2007), has been used to explain this and other similar choice inconsistencies. Query theory assumes that preferences, like all knowledge, are subject to the processes and dynamics of memory encoding and retrieval, and explores whether *memory and attentional processes* can explain observed anomalies in evaluation and choice. Weber et al. (2007) showed that the directional asymmetry in discounting is caused by the different order in which memory is queried for reasons favoring immediate versus future consumption, with earlier queries resulting in a richer set of responses, and reasons favoring immediate consumption being generated earlier for delay vs. acceleration decisions.

Neural Representation of Hyperbolic Discounting McClure et al. (2004) investigate the neural systems that underlie discounting the value of rewards based on the delay until the time of delivery. They test the theory that hyperbolic discounting results from the combined function of *two separate brain systems*}. The *beta system* is hypothesized to place special weight on immediate outcomes, while the *delta system* is hypothesized to exert a more consistent weighting across time. They further hypothesize that *beta* is mediated by limbic structures and *delta* by the lateral prefrontal cortex and associated structures supporting higher cognitive functions. Extending McClure et al. (2004), Finger et al. (2008) conducted an fMRI study investigating participants' neural activation underlying acceleration vs. delay decisions. They found hyperbolic discounting only in the delay, but not the acceleration, function.

3.2 Risk

Risk preference plays an important role in many agent-based economic models, in particular agent-based financial models. The frequently used assumptions are CARA (Constant Absolute Risk Aversion), CRRA (Constant Relative Risk Aversion), HARA (Hyperbolic Absolute Risk Aversion), and mean-variance, but, so far, few have ever justified the use of any of these with a neural foundation. This question can be particularly hard because, with the recent development of neuroscience, we are inevitably pushed to ask a deeper question: what the risk is. How does the agent recognize the risk involved in his or her decision making? What may cause the perceived risk to deviate from the real risk? Is there any particular region in our brain which corresponds to a different order of *moments*, the statistics used to summarize the probabilistic uncertainty?

3.2.1 Neural Representation of Risk

One of the main issues currently discussed in neuroeconomics is the neural representation of risk. Through a large variety of risk experiments, it can be shown that many different parts of the brain are involved in decisions under risk, and they vary with experimental designs. Based on the activated areas of the brain, one may define a neural representation of the risk associated with a given experiment. Different kinds of risks may be differentiated by their different neural representations, and different risk-related concepts may also be distinguished in this way. For example, the famous Knight's distinction between uncertainty and risk can now be, through delicate experimental designs, actually distinguished from their associated neural representations. Using the famous Iowa Gambling Task, Lin et al. (2008) show that uncertainty is represented by the brain areas closely pertaining to emotion, whereas risk is associated with the prefrontal cortex. In this vein, Pushkarskaya et al. (2010) distinguishes ambiguity from conflicts, and Mohr et al. (2008) separate behavioral risk from reward risk.

Identifying the neural representations of different risks may also shed light on the observed deviations of human behavior based on probability-based predictions. For example, a number of experiments, such as Feldman's Experiment (Feldman, 1962) or the Iowa Gambling Task (Lin, 2008), have indicated that even though subjects are given a risk environment, they may still behave as if they are in a uncertain environment. It is left for further study as to what are the neural processes behind this pattern recognition test which may inhibit or enhance the discovery of the underlying well-defined probabilistic environment.

3.2.2 Risk Preference

Different assumptions of risk preference, such as the mean-variance, CARA, CRRA, or HARA, are used in economic theory, usually in an arbitrary way. While agent-based modeling relies heavily on the idea of heterogeneity, preference or risk preference in most studies is normally assumed to be homogeneous. Little has been explored on the aggregate dynamics generated by a society of agents with heterogeneous risk preference.[iii] Nevertheless, it seems to be quite normal to see agents with heterogeneous risk preferences in neuroeconomic experiments (Paulsen et al., 2011).

Genetics have contributed in accounting for the difference in risk preference. Kuhnen and Chiao (2008) showed that several genes previously linked to emotional behavior and addiction are also found to be correlated with risk-taking investment decisions. They found that 5HTLPR ss allele carriers are more risk averse than those carrying the sl or ll alleles of the gene. D4DR 7-repeat allele carriers are more risk seeking than individuals without the 7-repeat allele. Individuals with the D2DR A1/A1 genotype have more stable risk preferences than those with the A1/A2 or A2/A2 genotype, while those with D4DR 4-repeat allele have less stable preferences than people who do not have the 4-repeat allele.

One of the essential developments in neuroeconomics is to provide neural foundations of the risk preferences. It is assumed that the human brain actually follows the finance approach, encoding the various statistical inputs needed for the effective evaluation of the desirability of risky gambles. In particular, neurons in parts of the brain respond immediately (with minimal delay) to changes in expected rewards and with a short delay (about 1 to 2 seconds) to risk, as measured by the payoff variance (Preuschoff, Bossaerts and Quartz, 2006). Whether one can find evidence of higher-order risk (skewness aversion, for instance) remains an interesting issue.

Some initial studies indicate that risk preference may be *context-dependent* or *event-driven*, which, to some extent, can be triggered by how the risky environment is presented. d'Acremont and Bossaerts (2008) show that the dominance of mean-variance preference over the expected utility depends on the number of states. When the number of states increases, it is more likely that the mean-variance preference may fit the data better than the expected utility.

4 LEARNING AND THE DRPE HYPOTHESIS

One essential element of agent-based computational economics is the notion of *autonomous agents*, i.e, the agents who are able to learn and adapt on their own. It would have been a big surprise to us if neuroscience had not cared about learning. However, it will also be a surprise to us if the learning algorithms which we commonly use for the software agents can actually have their neural representations. Nonetheless, a few recent studies have pointed in this direction.

Studies start with how the brain encodes the prediction error, and how other neural modules react to these errors. The most famous hypothesis in this area is the *Dopaminergic reward prediction error* (DRPE) *hypothesis*. This hypothesis states that neurons that contain the neurotransmitter release dopamine in proportion to the difference between the *predicted reward* and the *experienced reward* of a particular event. Recent theoretical and experimental work on dopamine release has focused on the role that this neurotransmitter plays in learning and the resulting choice behavior. Neuroscientists have hypothesized that the role of dopamine is to update the *value* that humans and animals attach to different actions and stimuli, which in turn affects the probability that such an action will be chosen. If true, this theory suggests that a deeper understanding of dopamine will expand economists' understanding of how beliefs and preferences are formed, how they evolve, and how they play out in the act of choice.

Caplin and Dean (2008) formulate the DRPE hypothesis in axiomatic terms. Their treatment has precisely the *revealed preference* characteristic of identifying any possible reward function directly from the observables. They discuss the potential for measured dopamine release to provide insight into belief formation in repeated games and to learning theory, e.g., *reinforcement learning*. Their axiomatic model specifies three easily testable conditions for the *entire class of reward prediction error (RPE) models*. Briefly, the axioms will be satisfied if activity is (1) increase wit prize magnitude (2) decreasing with lottery expected value and (3) equivalent for outcomes from all lotteries with a single possible outcome. These three conditions are both necessary and sufficient for any RPE signal. If they hold, there is a way of defining experienced and predicted reward such that the signal encodes RPE with respect to those definitions. Rutledge et al. (2010) used the BOLD responses at the outcome time to test whether activity in the nucleus accumbens satisfies the axioms of the RPE model.

Klucharev et al. (2009) show that a deviation from the group opinion is detected by neural activity in the rostral cingular zone (RCZ) and ventral striatum. These regions produce a neural signal similar to the prediction error signal in reinforcement learning that indicates a need for social conformity: a strong conflict-related signal in the RCZ and NAc trigger adjustment of judgments in line with group opinion. Using an olfactory categorization task performed by rats, Kepecs, Uchida, and Mainen (2008) attempt to obtain evidence for quantitative measurements of learning increments and test the hypothesis implied by the reinforcement learning, i.e., one should learn more when uncertain and less when certain.

Studies also try to find the neural representation of different learning algorithms. The commonly used reinforcement learning and Bayesian learning is compared in Bossaerts et al. (2008) where they address the existence of the dual system.[iv] They consider the *reflective system* and the *reflexive system* as the neural representation of Bayesian learning and reinforcement learning, respectively. Using the trust game, they were able to stratify subjects into two groups. One group used well-adapted strategies. EEG recordings revealed activation of a reflective (conflict-resolution) system, evidently to inhibit impulsive emotional reactions after disappointing outcomes. Pearson , Hayden, and Platt (2011) initiated another interesting line of research, i.e., the neural representations which distinguish *exploration* from *exploitation*, the two fundamental search strategies frequently used in various intelligent algorithms, say, genetic algorithms.

5 DUAL SYSTEM CONJECTURE

The dual system conjecture generally refers to the hypothesis that human thinking and decision-making are governed by two different but interacting systems. This conjecture has been increasingly recognized as being influential in psychology (Kahneman, Diener, and Schwarz, 2003), neural science (McClure, 2004), and economics. The two systems are an *affective system* and a deliberative system (Loewenstein and O'Donoghue, 2005) or a *reflexive system* and a *reflective system* (Lieberman, 2003). The affective system is considered to be myopic, activated by environmental stimuli, and primarily driven by affective states. The deliberative system is generally described as being goal-oriented and forward-looking. The former is associated with the areas of the brain that we have labeled the ventral striatum (nucleus accumbens, ventral caudate, and ventral putamen), the right striatum, neostriatum and amygdala, among others, whereas the latter is associated with the areas of the brain that we have labeled the ventromedial and dorsolateral prefrontal and anterior cingulate, among others.

The dual system of the brain has become the neuroeconomic area which economic theorists take the most seriously. This has also helped with the formation of the new field known as *neuroeconomic theory*. A number of dual-process models have been proposed in economics with applications to *intertemporal choice* (Loewenstein and O'Donoghue, 2005; Fudenberg and Levin, 2006; Brocas and Carrillo, 2008), *risk preferences* (Loewenstein and O'Donoghue, 2005), and *social preferences* (Loewenstein and O'Donoghue, 2005). All these models view economic behavior as being determined by the interaction between two different systems.

The application of the dual system conjecture to learning is just the beginning. Earlier, we have mentioned the cognitive loading between different learning algorithms, such as reinforcement learning vs. Bayesian learning (see Section 4). This issue has been recently discussed in experimental economics (Charness and Levin, 2005), and now also in neuroeconomics (Bossaerts et al.,2008).

5.1 Software Agents with Neurocognitive Dual Systems

While agents with dual systems have been considered to be a new research direction in neuroeconomic theory (Brocas and Carrillo, 2008a, Brocas and Carrillo, 2008b), software agents or autonomous agents in agent-based modeling mostly follow a single system. However, the dual system interpretation exists for many agent-based economic models. Consider the fundamentalist-chartist model as an example, where the fundamentalist's and chartist's behavior can be differentiated by the associated neural systems, say, assuming the former is associated with a deliberative system while the latter is associated with the affective system.

Another example is the *individual learning* vs. *social learning*. These two learning schemes have been frequently applied to model the learning behavior in experiments and their fit to the experimental data are different (Hanaki, 2005). Agent-based simulation has also shown that their emergent patterns are different. For example, in the context of an artificial stock market, Yeh and Chen (2001) show that agents using individual learning behave differently from agents using social learning in terms of market efficiency, price dynamics and trading volume. If individual learning can be associated with, say, the deliberative system, and social learning can be connected to the affective system, then the dual system can also be applied to agent-based modeling. This issue opens the future to collaboration between agent-based economics and neuroeconomics.

6 FROM MODULAR MIND/BRAIN TO MODULAR PREFERENCE

At present, modularity (Simon, 1965) is still not a part of agent-based economic modeling. This absence is a little disappointing since ACE is regarded as a complement to mainstream economics in terms of articulating the mechanism of evolution and automatic discovery. One way of making progress is to enable autonomous agents to discover the modular structure of their surroundings, and hence they can adapt by using modules. This is almost equivalent to causing their "brain" or "mind" to be designed in a modular way as well.

The only available work in agent-based economic modeling which incorporates the idea of modularity is that related to the agent-based models of innovation initiated by Chen and Chie (2004). They proposed a *modular economy* whose demand side and supply side both have a decomposable structure. While the decomposability of the supply side, i.e., production, has already received intensive treatment in the literature, the demand side has not. Inspired by the study of *neurocognitive modularity*, Chen and Chie (2004) assume that the preference of *consumers can be decomposable*.[v] In this way, the demand side of the modular economy corresponds to a market composed of a set of consumers with *modular preference*.

In the modular economy, the assumption of modular preference is made in the form of a dual relationship with the assumption of modular production. Nevertheless, whether in reality the two can have a nice mapping, e.g., one-to-one relationship, is an issue related to the distinction between *structural modularity* and *functional modularity*. While in the literature this distinction has been well noticed and discussed, "recent progress in developmental genetics has led to remarkable insights into the molecular mechanisms of morphogenesis, but has at the same time blurred the clear distinction between structure and function." (Callebaut and Rasskin-Gutman, 2005, p. 10)

The modular economy considered by Chen and Chie (2004) does not distinguish between the two kinds of modularity, and they are assumed to be identical. One may argue that the notion of modularity that is suitable for preference is structural, i.e., *what it is*, whereas the one that is suitable for production is process, i.e., *what is does*. However, this understanding may be partial. Using the LISP (List Programming) parse-tree representation, Chen and Chie

(2004) have actually integrated the two kinds of modularity. Therefore, consider drinking coffee with sugar as an example. Coffee and sugar are modules for both production and consumption. Nevertheless, for the former, producers add sugar to coffee to deliver the final product, whereas for the latter, the consumers drink the mixture knowing of the existence of both components or by "seeing" the development of the product.

Chen and Chie (2007) tested the idea of augmented genetic programming (augmented with automatically defined terminals) in a modular economy. Chen and Chie (2007)considered an economy with two oligopolistic firms. While both of these firms are autonomous, they are designed differently. One firm is designed with simple GP (SGP), whereas the other firm is designed with augmented GP (AGP). These two different designs match the two watchmakers considered by Simon (1965). The modular preferences of consumers not only define the search space for firms, but also a search space with different hierarchies. While it is easier to meet consumers' needs with very low-end products, the resulting profits are negligible. To gain higher profits, firms have to satisfy consumers up to higher hierarchies. However, consumers become more and more heterogeneous when their preferences are compared at higher and higher hierarchies, which calls for a greater diversity of products.[vi] It can then be shown that the firm using a modular design performs better than the firm not using a modular design, as Simon predicted.

7. CONCLUDING REMARKS: AGENT BASED OR BRAIN BASED?

Can we relate agent-based economics to brain-based economics (neuroeconomics)? Can we use the knowledge which we obtain from neuroeconomics to design software agents? One of the features of agent-based economics is the emphasis on the *heterogeneity* of agents. This heterogeneity may come from behavioral genetics. Research has shown that genetics has an effect on our risk preference. Kuhnen and Chiao (2008), Jamison et al. (2008), and Weber et al. (2008) show that preferences are affected by the genes and/or education (environment). With the knowledge of genetics and neuroeconomics, the question is: How much more heterogeneity do we want to include in agent-based modeling? Does it really matter?

Heterogeneity may also result from age. The neuroeconomics evidence shows that certain functions of the brain will age. The consequence is that elderly people will make some systematic errors more often than young people, and, age will affect financial decisions as well (Samanez Larkin, Kuhnen, and Knutson, 2008). Thus the same question arises: when engaging in agent-based modeling, should we take age heterogeneity into account? So, when a society ages, should we constantly adjust our agent-based model so that it can match the empirical age distribution of the society? So far we have not seen any agent-based modeling that features the aspect of aging.

Neuroeconomics does encourage the modular design of agents, because our brain is a modular structure. Many different modules in the brain have been identified. Some modules are related to emotion, some are related to cognition, and some are related to self-control. When human agents are presented with different experimental settings, we often see different combinations of these modules.

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[i] See also Baldassarre (2007). While it has a sharp focus on the *economics of happiness*, the idea of building economic agents upon the empirical findings of psychology and neuroscience and placing these agents in an agent-based computational framework is the same as what we argue here. From Baldassarre (2007), the reader may also find a historical development of the *cardinal utility* and *ordinal utility* in economics. It has been a while since economists first considered that utility is a very subjective thing which cannot be measured in a scientific way, so that interpersonal comparison of utility is impossible, which further causes any redistribution policy to lose its ground.

[ii] It is not clear where preferences come from, i.e., their formation and development process, nor by when in time they come to their steady state and become fixed. Some recent behavioral studies have even asserted that people do not have preferences, in the sense in which that term is used in economic theory (Kahneman, Ritov, and Schkade, 1999).

[iii] For an exception, see Chen and Huang (2008).

[iv] See Section 5 for the dual system conjecture.

[v] Whether one can build preference modules upon the brain/mind modules is of course an issue deserving further attention.

[vi] If the consumers' preferences are randomly generated, then it is easy to see this property through the combinatoric mathematics. On the other hand, in the parlance of economics, moving along the hierarchical preferences means traveling through different regimes, from a primitive manufacturing

economy to a quality service economy, from the mass production of homogeneous goods to the limited production of massive quantities of heterogeneous customized products.