Simulating Lifetime Saving Decisions: The Behavioral Economics of Countervailing Cognitive Biases

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***Summary**: Behavioral Economics has a rich tradition of empirical studies involving the effects of personal decision biases involving trade-offs between future and present utility values. Although research in the area has identified several psychological biases in the decision making process, most research explores one bias at a time, given the computational complexity of considering more than one, among other reasons. This program of research proposes to create a numerical platform for exploring the implications of how countervailing biases may interact to create unexpected outcomes when two or more biases are present at the same time. It will use life-time savings decisions as a theoretical domain since both theory and empirical studies are well-developed. Our program of research involves four main stages: 1) analyzing the "Individual Utility Function" model in behavioral economics, 2) developing a simulation platform to explore strategies to maximize lifetime utility incorporating four biases widely-explored in the behavioral economics literature, 3) using the platform to explore main interactions among the four biases, and 4) reflect on the process and results to contribute to the field of behavioral economics. In this paper, we introduce these four steps, and also discuss initial progress in stages 1 and 2.*

Background of the Problem

Biases that are generate by suboptimization in a dynamic context require fixes in following time periods (Conlisk, 1996). This concept reminds the postulate of feedback loops in System Dynamics. In *Industrial*

Dynamics, Forrester claims that the obsession with "optimum" solutions has caused the bias of much today's management science toward mathematical rather than managerial motivation (Forrester, 1961). Even after six decades, it seems that this assertion holds in majority of the time. In the first chapter of the same book, he introduces the concept of servo-mechanisms (or information-feedback systems) as the most important foundation of industrial dynamics. Suboptimization with feedback was also studied by Day and colleagues in a broad and coherent approach, called "Recursive Programming" (Day 1963; Day and Cigno 1978).

We have a very strong background in finding the optimal solution in vast majority of economical systems and games. Relying on this strong asset, one may ask "why do we need to study and model the suboptimal solutions that are grounded on indistinct hypotheses lacking inclusive cohesion and scientific background? Even if we agree upon the fact that the in suboptimal solutions the reasoning are not scientific enough and they are based on a tangled mess, it does not mean that the optimal solutions are any better in this perspective. To get to the point that we can conduct current known optimization methods, we need to simplify the problem until it is devoid of practical interest (Forrester, 1961). All the assumptions that we make to reach the clean optimizable models deviates us from the real problem that we were facing in the first place. "Perfect information" and "unbounded rationality" are the examples these phony systems that only exist on paper. One unneglectable factor that forces us to be boundedly rational is deliberation cost. Rule of thumbs and heuristics usually are as sufficient as optimal solution whereas they are quick and less expensive (Conlisk, 1996). As we can see there is tradeoff between cognitive effort and judgmental accuracy (Pitz and Sachs, 1984). If we really want to optimize a system, we also need to optimize the deliberation cost, which as a new variable will need its own deliberation cost optimization. This series of optimization can go for ever and create an infinite intractable regress (Savage 1954; Winter 1975; Day and Pingle 1991).

In most economic models, we restrict the choices and tighten the system boundary in order to make it mathematically possible to optimize over a specific variable. For suboptimization many other details will be added to the model that will give the subject numbers of decision choices. In other word suboptimization will add to the degrees of freedom in the system. In the presence of this abundant degrees of freedom finding the best solution is extremely difficult, if not impossible. Nonetheless, mathematics alongside with computers could help experts to run more complex algorithms and optimization techniques. Using these new tools, it is possible to tackle problems which used to be unsolvable in the past (Stachurski, 2009). Without computers, empirical researchers used to add dynamic and stochastic elements as afterthoughts to raw outcomes of static, deterministic economic models. However, with new simulations, it is now possible to explore and test powerful theories about rational economic agents operating through time in stochastic environments (Stokey, 1989). There are many different methods for theoretical models, in which we see complicated stochastic processes to investigate economics behaviors. We can track the history of these theoretical developments over time by reviewing the literature. Ramsey (1928) and Hotelling (1931) firstly established the economic applications of the calculus of variations. Later on, the contingent-claim view of economic equilibria was introduced by Arrow (1953) and Debreu (1959). The contribution of Bellman (1957) and Blackwell (1965) was the theory of dynamic programming. In 1989, Stokey studied the Recursive Methods in Economic Dynamics.

The ultimate goal in this program of research is to provide a numerical platform for simulation-based exploration of theoretical ideas that are grounded in the modern economic dynamics. Our approach contributes to the literature on behavioral economics because it provides researchers with graphical representations that will potentially help the exploration of more complex models, and also through these visualizations reach a wider audience of researchers that may apply behavioral economics models to domains such as natural resource management. In addition, these simulations can support both deterministic and stochastic dynamic economic problems, problems facing certainty or uncertainty, and finally problems in either finite horizon or infinite horizon. Combined with the System Dynamics concepts such as accumulation, feedback loops, delay, and graphs over time, economic dynamics would carry new hypotheses which can be tested in a computational experimental environment.

To explain how System Dynamics models can help us to better understand a behavioral economics problem, we started with a well-established macroeconomics problem. Maximizing the lifetime utility of an individual's consumption behavior is an example of many other concepts in economics that can be studied this way. This example also serves to illustrate the kinds of substantive economic questions are drawn from the much longer list of applications to be treated in detail in later researches.

The rest of the paper is organized in three additional sections. Section 2 describes our theoretical motivation. Section 3 reports on our current progress in the development of our numerical simulation platform. Finally, section 4 briefly describes the implications of our current results.

System Dynamics and Bounded Rationality

For several decades economic models were built upon subject's unbounded rational behavior. Still this notion is dominant among the economists, however, this trend is not as popular as it used to be. In his classic paper, John Conlisk (1996) mentions the abundance of empirical evidence as one the four reasons for incorporating bounded rationality in economic models. The bias evidence implies that individuals can make a wide range of significant and systematic cognitive or mental errors in economic decisions. The extent and grounds of these errors are themselves systematically relevant to economic settings such as deliberation cost, incentives, and experience. With this perspective, bounded rationality is not only redundant but also a required extension of economic reasoning.

In science and engineering, systematics error are known as biases. Many laboratory experiments addressed these substantial biases in human behavior in face of micro and macroeconomic decision-making processes (see Grether and Plott 1979; Nisbett and Ross 1980; Hogarth 1980; Tversky and Kahneman 1982; Slovic and Lichtenstein 1983; Pitz and Sachs 1984; Arkes and Hammond 1986; Plott 1986; Smith 1986; Slovic, Lichtenstein and Fischhoff 1988; Loewenstein and Thaler 1989; Tversky and Thaler 1990; Kahneman, Knetsch, and Thaler 1991; Herrnstein and Prelec 1991; Payne, Bettman, and Johnson, 1992; Grether 1992).

In System Dynamics literature, we can find many papers that suggest the notion of systematic errors in decision making process. For example, Sterman (1989) studied common “Misperceptions of Feedback” in an experiment, in which subjects are asked to manage a simulated inventory distribution system. The results of this experiment show that subjects do not behave optimally even when provided with perfect information and knowledge of system structure. Failure in understanding the feedback between decisions and the environment generate this bias.

Another important feature in System Dynamics can be the bottom line of biases, accumulation. In different contexts such as bathtub dynamics, regulating body weight by adjusting diet and exercising, adjusting personal savings to a desired level after a major unexpected spending, or understanding changes in the level of CO_2, people frequently make mistakes in their expectations and consequently their decisions (Booth Sweeney and Sterman, 2000; Cronin et al., 2009; Sterman, 2008; Abdel-Hamid et al., 2014; Sterman, 2010; Baghaei Lakeh and Ghaffarzadegan 2015).

Biases and their causes have been investigated in a variety of studies. In most of these studies the biased judgements have been compared to the optimal decisions. In other words, at the end the subjects were given guidelines and tools (such as simulation) to become unbounded rational people. However, what seems to be missing is why subjects have these biases in the first place. How their mental model creates the structure of biased suboptimal decisions? This program of research tries to create a numerical platform in the context of “Individual Welfare Function” to show how human mind make suboptimal decisions.

2. A Multi-Step Research Program

2.1 Step one: Analyzing the “Individual Welfare Function” Model in Behavioral Economics.

We will use one of the better studied areas within behavioral economics, the problem of deciding how much to save for the future. The model that is presented here starts from one of its simplest version. To simplify the model we need some assumptions to make.

People live T periods, and retire in period τ. In each period $t < \tau$, they get some noisy income realization and earn some noisy investment income. They then decide how much to consume and how much to invest. In periods τ to T, the only source of income is investment income. One modeling decision is whether to give them a choice between a liquid and an illiquid asset to invest in. Another modeling decision is whether to give them a risky asset and a safe asset. Individuals may deal with a safe liquid asset, like government bonds, or a risky illiquid asset, like housing.

Current assumptions are as follow: 1) τ=T, which means individual will have income in all time periods. 2) income increases with a steady growth rate, 3) the investment interest rate (r) is a constant, 4) we started with only one type of asset.

Fully Rational Model

The model will run for T+1 number of time periods. Each individual start working at t=0 and dies at=T. The purpose of the model is maximizing the *Lifetime Utility (U).* Lifetime utility is the extent of happiness the household derives from its consumption. *Instantaneous Utility (u)* is how much utility the household gets in a given period by its *consumption (c_t)* in that period. The *discount factor (δ)* is how much less people care about the future compared to the present. The discount factor is a value between zero and one ($0< \delta<1$). *Coefficient of relative risk aversion (ρ)* is how much someone dislikes fluctuations in consumption. *Labor income (Y_t)* is what the person receives in each period and it excludes the *interest income (r)*. In this model, we assumed that the income grows with the constant rate of *G*.

$$Y_t = GY_{t+1}$$

Utility increases as the individual consumes more. However, consuming the first unit of goods yields more utility than the second unit. In general, by consuming more, the utility increases at a decreasing rate. There are numbers of utility functions that can reflect this effect. The following equation is one of the popular utility functions which is also known as iso-elastic utility function (or constant elasticity).

$$U(\{c_t\}) = \sum_{t=0}^{T} \delta^t u(c_t) = \sum_{t=0}^{T} \delta^t \frac{c_t^{1-\rho}}{1-\rho}$$

With this utility function, we will have:

$$u'(c) = c^{-\rho}$$

The Constraint is the income process. In each time period, we can calculate the corresponding wealth (W_t) by using:

$$Wt = (1+r)\,(W_{t-1} + Y_{t-1} - c_{t-1})$$

Optimal solution

The optimal dynamic programming solution has people saving to finance consumption in retirement and as a precaution against negative income shocks. You backwards induct a decision rule about how much to consume each period as a result of inherited wealth and any state variables about the income process. For simplicity purposes we did not consider state variables in income.

The solution for this optimization method is the “Euler Equation”:

$$u'(c_t) = \delta(1+r)Gu'(c_t+1)$$

$$c_t^{-\rho} = G\delta(1+r)c_{t+1}^{-\rho}$$

$$\left(\frac{c_{t+1}}{c_t}\right)^{\rho} = G(\delta(1+r))$$

For finite horizon model, you would backwards induct to get the solution to how much to consume any given wealth state. Individuals will not save for the time after T+1. So, in the last period, the individual will consume everything that is left[1].

2.2 Step Two: Developing a Simulation Platform.

The Simulation model should exactly captures important aspects of economic theory in the domain of lifetime savings. Based on the theory and current assumptions, we expect from the model that an individual save more in the early and middle ages of his lifetime and he will consume his savings at the end.

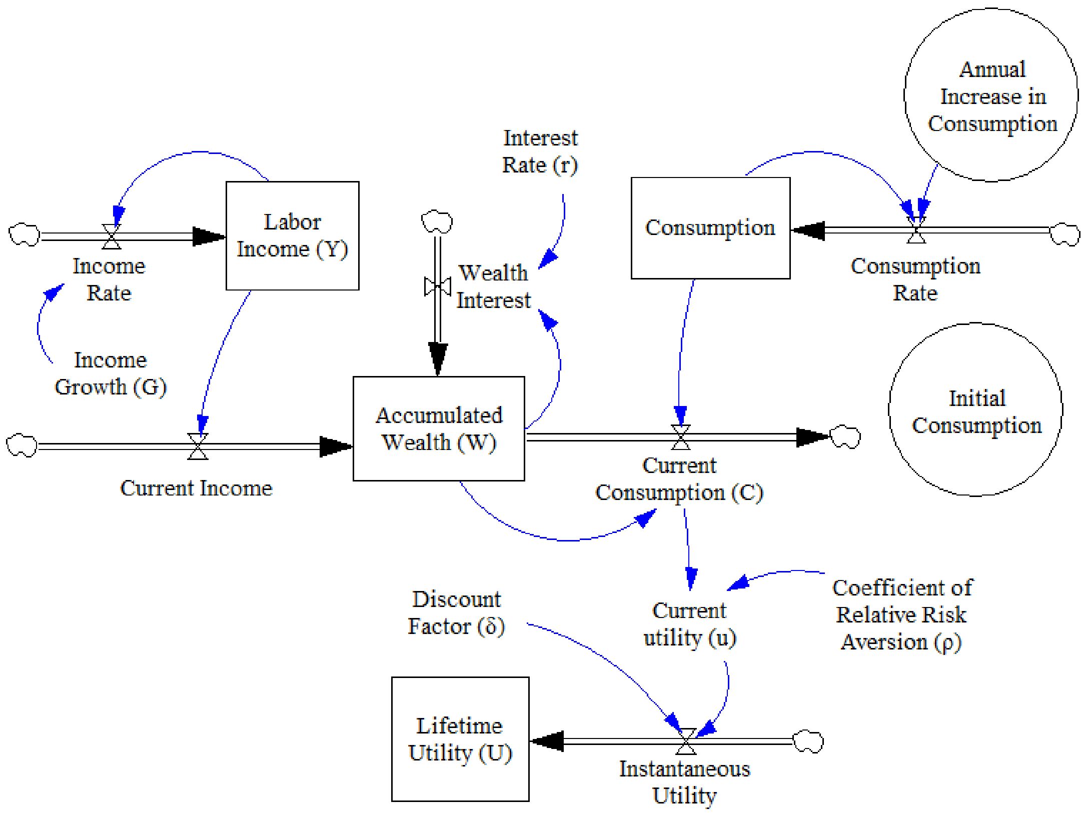


Figure 1. The SD translation of "Individual Welfare Function" Model

[1] For an infinite horizon model, one would use numerical dynamic programming methods to compute the fixed point of the Bellman equation.

$$V(W_t) = max\, u(c_t) + \delta V(W_{t+1} + Y_{t+1} - c_{t+1})$$

Each equation in this model has an equivalent in the behavioral economic model which was discussed in the first step. But how do we know whether our simulation shows the exact same results that we captured from the first step? In the first step, we claimed that the optimal consumption behavior should follow the Euler Equation. To build confidence in our model, we will optimize it subject to the two exogenous variables that are used in the Euler equation, the *Initial Consumption* and the *Annual Increase in Consumption (AIC)*. If the outcomes optimization equals the values that the Euler equation suggests, our model is correct. The other check can be the behavior of the *Accumulated Wealth (W)*. This variable should create a complete or a skewed bell-shaped graph over time. In addition, it should get the minimum value at the final step, as the person cannot consume after his death. The followings are the outcomes of our models which perfectly matches our validation scenarios:

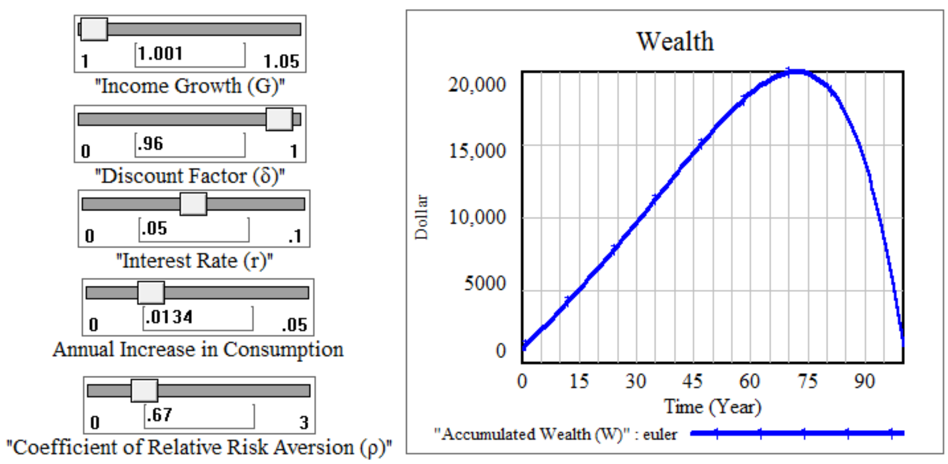


Figure 2. The Behavior of Accumulated Wealth over time based on variable shown on the left.

In the model, the individual will have an income even in the last time step. So, wealth in the last time step is not exactly zero. It equals to the income in that time step.

In this model, the equation for *Consumption Rate (CR)* is:

$$Consumtion\ Rate = Consumption * Annual\ Increase\ in\ Consumption$$

Using the mathematical equations behind this formulation, we will have:

$$c_{t+1} - c_t = c_t * Annual\ Increase\ in\ Consumption$$

$$c_{t+1} = c_t * (Annual\ Increase\ in\ Consumption + 1)$$

$$\frac{c_{t+1}}{c_t} = \ (Annual\ Increase\ in\ Consumption + 1)$$

$$\left(\frac{c_{t+1}}{c_t}\right)^{\rho}_{simulation} = (1 + Annual\ Increase\ in\ Consumption)^{\rho}$$

$$\left(\frac{c_{t+1}}{c_t}\right)^{\rho}_{Simulation} = (1 + 0.0134)^{0.67} = \ 1.009$$

$$\left(\frac{c_{t+1}}{c_t}\right)^{\rho}_{Euler} = G\big(\delta(1+r)\big) = (1.001) * (0.96) * (1 + 0.05) = 1.009$$

Since the value from the simulation equal the value derived from the Euler equation, we can claim that the simulation can mirror the results of the first step.

2.3 Further research

Step Three: Use the Platform to Explore Four Biases. This step replicates research from Step one, but finds a way to analyze and present interactions between all four biases. Behavioral biases: we want to have consumers form their solutions in the face of four counter-vailing biases:

1) **Present-biased preferences** (a.k.a. hyperbolic discounting): the IWF either doesn't have a preference over the T periods or has a fixed exponential discount rate (so it might value a util in period 30 as only δ^{30} as much as a util in period 1, where $0 < \delta < 1$). With present-biasedness, an agent discounts period 30 as $\beta\delta^{30}$, where all future periods are discounted by a hyperbolic discounting factor $0 < \beta \leq 1$. This creates time inconsistency, where people want to save for the future when they are comparing two future periods, but generally want to consume today when comparing today to a future period.

Effect on savings: shift savings to the illiquid asset
decreases savings

2) **Overconfidence:** agents think their actual market return will be higher than it actually is.

   Effect on savings: increases savings

3) **Myopic loss aversion:** agents face a jolt of disutility based on how much their savings go down between periods t and t+1.

   Effect on savings: shift savings to the safe asset
   decrease saving

4) **Projection bias:** agents expect their future needs and incomes to be similar to current needs

   Effect on savings: Shift savings to the illiquid asset
   Decreases precautionary saving

Each of these biases is defined by a single parameter. There is thus a vector of four behavioral parameters, θ. For any given vector θ, an individual would have a different savings rule mapping the time period t, current wealth level, and current income level into consumption and investment decisions. That rule then produces a consumption stream {c}, which can be plugged into the Individual Wealth Function to get a total value.

We want the simulation to be able to map the space of θ. Under standard behavioral economic modeling, increasing any bias always makes people worse off. If multiple biases push in different directions, then there should be regions where increasing one of the biases makes people better off. Then, we will look for local maxima in the space of θ; at such points, a policy to reduce the impact of a bias would reduce their welfare. Using this method will give us a policy tool (such as illiquid savings accounts) and an opportunity to look at what parameter regions tend to make them a good idea.

Introducing errors in perception of different parameters

Including even one of these biases will force the model to include more detail and complexity. In order to obtain more confidence in the model and to get a sense of countervailing forces, we tried a simple scenario in which an individual misperceives two of the parameters in Euler equation. Among the four constants in the equation the Coefficient of Relative Risk Aversion {ρ} (CRRA) and the Interest Rate {r} were chosen. In this set of experiment we are eager to examine how overconfidence in interest rate offset misperception of personal level of risk comfort and vice versa.

Based on the Euler equation we know that for each misperceived interest rate {r'} there would be a misperceived CRRA {ρ'} which can cancel out the impact of the former misperception. It is also true when we misperceive CRRA.

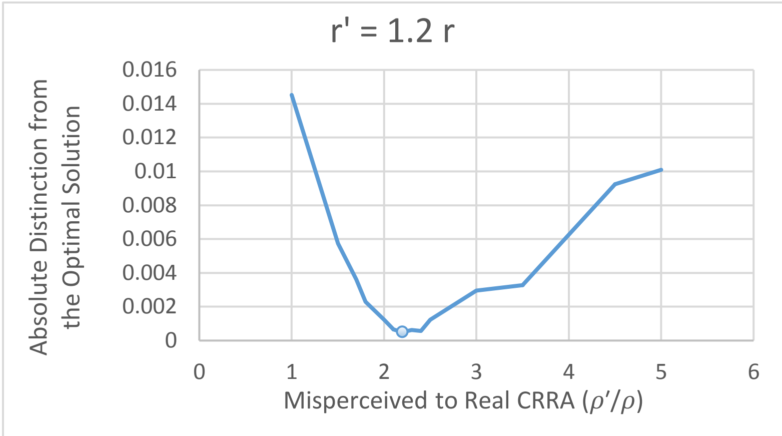
$$(eq.1) \qquad r' = \frac{\left(\delta(G)(1+r)\right)^{\frac{\rho'}{\rho}}}{\delta(G)} - 1$$

$$(eq.2) \qquad \rho' = \log_{(\delta(G)(1+r))}\left(\delta(G)(1+r')\right)^{\rho}$$

For example, among all the individuals who fit the settings[2] given in Figure 2 and who believe the interest rate is 20% higher than what it really is, only those can gain the optimal utility that also misperceive their CRRA to be 2.057 times more than it really is. With the same settings, the optimal will be captured if an individual misperceives CRRA to be 20% higher and the interest rate to be 3.8% higher simultaneously. To test the model, we changed one of these two variables and mapped the Utility {U} based on the different

[2] Income Growth (G) = 1.001
Interest Rate (r) = 0.05
CRRA (ρ) = 0.67
Discount Factor (δ) = 0.96

values of the other parameter. For the 20 percent change in each parameter, the graphs in Figure 3 were produced.



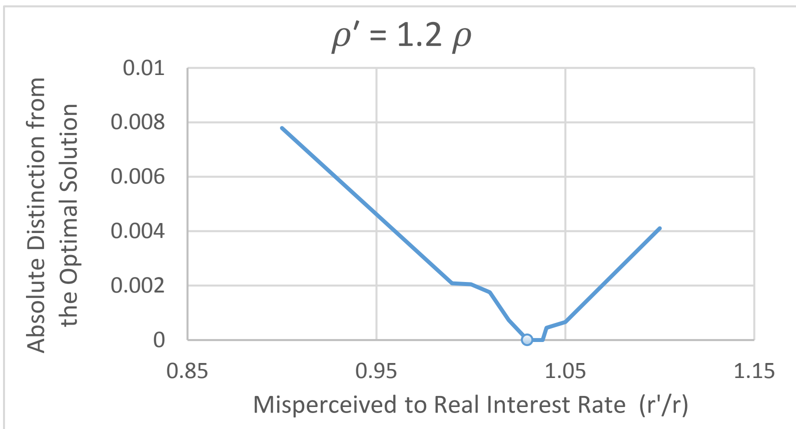


Figure 3. The absolute discrepancy between the "*Optimal Annual Growth in Consumption*" and the "*Real Annual Growth in Consumption*" in different scenarios where the interest rate and the Coefficient of Relative Risk Aversion are perceived to be 20% higher respectively.

For each point on the graphs, we chose the optimum payoff in at least one million random tries for the two constraints in the Euler equation: The Annual Growth in Consumption (AGC) and the Initial Consumption. When misperceiving the interest rate, if we choose a right value for CRRA, there should not be a change in the optimal AGC. Based on the following series of equations, the Optimal AGC and the Real AGC should be the same. The same conclusion hold when we misperceive the CRRA.

From Euler Equation we have:

$$\frac{c_{t+1}}{c_t} = \left(\delta(G)(1+r)\right)^{\frac{1}{\rho}} = \left(\delta(G)(1+r')\right)^{\frac{1}{\rho'}}$$

And from the model we could prove that

$$\frac{c_{t+1}}{c_t} = 1 + Annual\ Growth\ in\ Consumption$$

These two equations imply that our experiment does not guarantee that the initial consumption will be the same, however, the AGC should be almost equal to the optimal. Figure 3, shows that for the values that we were expecting from equation 1 and 2, the discrepancy between the optimal and the Real AGC is zero or reasonably close to zero.

Step Four: Theoretical Elaboration. Steps one and two are built on a numerical platform that accepts all of the assumptions of the standard economic model as well as empirical research on behavioral biases. When viewed from a SD perspective, these frames are low on implicit feedback effects. But our numerical platform has been cast exactly in the form a system dynamics model, so it will cry out for addition of dynamic hypotheses that rely on feedback mapping. The contribution here will be an elaboration of existing theory in behavioral economics, leading to proposing empirical methods for testing these new dynamic hypotheses.

3. Implications of this Research Program

The Choice of Discount Rate

Intergeneration discounting has always been a controversial topic in economy since Böhm-Bawerk (1889) and Fisher (1930) invented intertemporal preference. How to measure a discount rate is both empirical and ethical. The balance of our bank savings to be used in future, and the amount we spend in each time period shows the tradeoff between present and future which represents the idea of how choice of discount rate is empirical. It is also ethical as we decide about the distributions of resources and intertemporal goods and service between generations. A rational-chosen discount rate or discounting approach must consider both empirical and ethical at the same time and they should not overrule each other. (Tol, 1999).

There are lots of arguments regarding the discount rate between generations:

- Discounting is inappropriate for intergenerational issues. Utility discount rate appraises definite distance and we are not able to emphatically distinguish future. (Schelling, 1995.)
- The implicit assumption in standard discounting that designated capital transfers between generations are possible, seems to be somewhat incorrect (Lind, 1995)
- The postulate of discounting losses of ‘natural capital’ is to be rejected in principle. Lowering the discount rate cannot effectively justify the irreversible losses (Daly and Cobb, 1989).
- While discounting with given generation is appropriate, it is not applicable between generations.

Intergenerational externalities is another issue that comes with the discounting and arises because future generations do not play a part in the decision-making processes that will impact them. While today’s decisions can have irreversible consequences on them, they cannot defend their interests (Padilla, 2002). To be straightforward, it means that we expect our children to pay for our (over-)consumption of natural resource.

We can refer to sustainability as preventing the dominance of the preference of the current generation over the the preference of future generations. This axiom was used in Chichilnisky’s intertemporal welfare system (Chichilnisky, 1996). In System Dyanmics, sustainability as described above, has been studied and used repeatedly. One of the good examples, is Tom Fiddaman’s FREE (Feedback-Rich Energy-Economy) model which he used in his thesis (Fiddaman, 1997). Sustainability and climate change, as one of the intergenerational issues, have been modeled in different studies (IPCC, 1996, 2001; Weitzman, 2001; Nordhaus, 1997; UNEP, 1987). However, in the FREE model a special consideration has been given to the concept of discount rate. Different approaches and different values were examined in well-designed scenarios.

"Fair discounting and consideration of intangible damages substantially raise the … abatement effort. In both deterministic and uncertain cases, near-term inaction is a poor policy."

Many discounting approaches have been suggested and investigated by different scholars (Sumalia and Walters, 2005; Cline, 1992; Heal, 1997, 1998; Weitzman, 2001; Chichilnisky, 1996; Rabl, 1996; Fearnside, 2002; Collard, 1978; Bellinguer, 1991; Nijkamp and Rouwendal, 1988), however the mystery of discounting rate still holds for governments, corporations, and even individuals. The emphasis on the current versus future generation interest can be considered as a policy rather than a scientific question (Fearnside, 2002). Although numbers of researchers sought to determine a fitting discount flow of benefits in order to more adequately take into account the interests of future generations, authors could not find any effort on finding why we cannot reach even most conservative views of discounting when it comes to natural resources and environment. This issues is also tied with ethical grounds. Regardless of how we have defined our discounting method, it will create negative externalities for generations to come, if we cannot practically grasp it.

There is a consensus of opinion among ninety-seven percent of climate scientists that global warming trends are very likely due to human activities (Global Climate Change, 2016). In addition, in nowadays life, we hear news about the impacts of climate change on a daily basis. Yet, we have failed to adapt our CO_2 emissions to pursue sustainability. Unfortunately, this kind of behavior is not limited to the climate change. Almost all natural resources are being overexploited and many have already been exhausted. Based on the short- and especially long-term outcomes of the decisions that we, as the current generation make, it is now obvious that we are not even close to an ethical fair relation with the next generations. While the current generation as a whole seems to be behaving unfairly, most of individuals as the contributing subjects does not want to be unethical. The question is why ethical people make unethical choices?

There are lots of cases in System Dynamics literature, were the elements of a system try to optimize their behavior, whilst the whole system as a whole fails to be optimum (e.g. Beer game). That is where we learn the postulate of “systematic errors” or “biases”. In this program of research we are trying to answer to the mentioned question within this perspective. If we can include these systematic errors in the perception of decision-deriver factors of our environment into our calculations, then not only we will have a more accurate discounting approach, but also we will gain a better understanding of how to actually implement it through practical policies.

The Problem in Brief

While there is a strong tie between social sciences and engineering designs, especially in macro levels, most of the time this bond has been neglected in these studies because of the extra complexity that it adds to the system. It is very rare to see a social analysis of constructing a reservoir in engineering models. On the other hand, social scientists also usually have a hard time to follow the cost-benefit analysis done by engineers. The lack of a comprehensive study can lead to two opposite direction in making the best decision for policy makers. The equations may suggest that we should stop transferring water to an area whose farming is less profitable and more water-consuming than another area. Nonetheless, it can become a social disaster for the farmers of that area, who now need to change their jobs and even their home town. In some cases, some farmer families have been farming for thousands of years on the same farm. They literally do not have any other skill rather than farming and gardening. If the government cuts their water resources, it has to face numbers of angry jobless non-skilled citizens who have been excluded from designing calculations.

In another example in designing a water reservoir, engineers calculate its capacity based on the available water (supply) and demand. The calculations are strongly math-intensive and grounded on years of research and experiment, yet there are numbers of dams that are barely half full and sometimes have never reached their highest capacity. Most of the time droughts and climate change are blamed – which are also a long-term consequence of human activity that should be included in the analysis – but there might be a simple hidden reason for this similar behavior. Dams cut the water flow to the downstream areas and make those area socially and economically less attractive. People will start to migrate to upstream lands and will increase the demand for water. As more water get consumed in upstream, less water will be accumulated behind the dams. In addition, this dynamic will add other constructions that was not included in the initial calculations of reservoir's design.

Many other cases can be found that explains why we need multidisciplinary analysis for macro level decisions. In the engineering calculations, engineers use very complex models to optimize systems in public's favor. Spending so much energy and time, they come up with precise optimized result number with several decimals. But unfortunately, when it comes to governors to make decisions, they usually need to sacrifice most of this precision as they need to include the probable social impacts of their decision.

One of the main reasons that engineers and experimental scientists are hesitant to proceed further than pre-fixed system boundaries is that even the slightest inclusion will increase many degrees of freedom in normal optimization processes. Especially in numerical analyses the optimization may exponentially get more intensive by adding each degree of freedom.

While modeling the behavioral dynamics is still extremely complex, this program of research tries to build a numerical platform for different generic cases, in which subjects want to optimize their lifetime utility.

The purpose of our proposed research program is to develop a numerical platform that uses simulation to facilitate experimentation of complex models in Behavioral Economics. Our final vision involves the development of a platform that can be used to test interactions between four well-researched biases in human decision making.

Although our research is still in early stages, we believe that the results are promising. We have developed an initial prototype that proves that it is possible to model and optimize the basic assumptions in behavioral economics with regards to wealth, consumption, income and lifetime utility. Our results suggest that it is possible to develop a more tightly coupling of system dynamics simulation with empirical work in behavioral economics, adding both theoretical insight, suggesting new pathways for research, and opening new domains for future research.

A great variety of economic and other decision-making problems are quite naturally cast in a recursive framework. Many of these problems, especially those regarding our consumption decisions on natural resources, are particularly relevant in the current discussions on sustainability and development.

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