Toward a "Choice Cost Economics": A Positive and Generalized Model of Rational Choice for Institutional Economics

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This paper introduces a simple, positive model of choice that is empirically grounded in the natural blind search mechanisms that are fundamental in all biological and evolutionary processes. This generalized rational choice model can be explicitly derived from the standard rational choice model by converting its implicit fixed assumptions into explicit variables, such as nonzero times and costs to evaluate choices. One novel implication of recognizing positive "choice costs" is that the human mind no longer has an insurmountable competitive advantage in its ability to do choice evaluation. The "rational" calculation of optimal potential actions might be more efficiently accomplished with faster, cheaper or better processes for choice evaluation that operate outside the mind. In other words, a theory of economic substitutes emerges for rational choice, ranging from traditional rational choice, which is 100% vicarious trials of choices in the mind, to 100% actual choice trials in the real world. Countless substitute methods for evaluating choices are predicted (and observed) to appear between these endpoints, but have been previously ignored. Many real institutions can be freshly understood as manifestations of efficient serial (and parallel) allocation of blind choice trials among search stages with economic tradeoffs: from low costs and times to evaluate a choice with low predictive accuracy, to higher costs, times and accuracies up to the full-cost trials of real actions.

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INTRODUCTION

"We cannot even begin to explain behavior, until we are confident that we have adequately described it..."-- John Dupre

We can agree that you are reading this sentence by your own premeditated choice and not by some purely random chance - that much should be uncontroversial. But you cannot be reading this sentence because of your own *rational* choice, at least not as traditionally conceived in economics. Reading this sentence cannot be an optimal choice of "words to read" from a set of predetermined text choices with known expected value, because you did not (and could not) know the words in this sentence until you were actually reading it. The same is also true for this sentence and all that will follow: there is no advance calculation by which you can know their expected value to you. You are "flying blind", word by word, and hoping for a decent eventual payoff even though you still might not know whether reading this paragraph has been a good idea.

This perceived fundamental blindness to the ex post result of your ex ante reading choice is in fact real and incurable, as it is for all your chosen actions to some degree. As Karl Popper famously noted: "*We do not know: we can only guess.*" (p278: 1965). But this epistemological handicap does not block real choice mechanisms from operating or doom us to random acts. Fortunately, for the economic profession (and many others), we seem to behave and choose in mostly predictable, nonrandom ways. The path you followed to get to this word in this paper was decidedly not a random walk or a singular blind shot in the dark. You were actively in control and deliberately choosing actions at each step. You find yourself reading this sentence as the result of a well-defined *adaptive* choice process that turns out to be both fundamentally rational *and* fundamentally blind, as this paper will explain.

Smith (2003, 2008) has masterfully discussed these two ostensibly opposed views of choice as constructivist forms of rationality (rational choice models), versus ecological forms of rationality (unconscious behavioral fit to environments). This paper aims to build on that project and the specific strands of literature contained within it. These include non-rational choice (Alchian, 1950, Becker, 1962, Gode and Sunder, 1993), economic search (Stigler, 1961, 1962, Weitzman, 1979) and decision-making under ignorance (Hayek, 1945, Simon, 1955, Telser, 1973, Loasby, 1976)[1]. At one typical modeling extreme we have an ecological rationality where the

[1] Economists have traditionally conceived of search as probabilistic, even where distributions are unknown (Rothschild, 1974). Biologists have historically done a much better job of analyzing choice under ignorance due to their animal subject matter. Evolutionary game theory approaches (Maynard-Smith, 1982), a collaborative effort with economics, has proven to be the leading way to usefully model adaptive, non-rational choice. Computer science turns out to be an equally insightful source of concepts in this area, particularly system dynamics and control (Ashby, 1960, Holland, 1975) and genetic algorithms (Goldberg, 1989).

environment acts on some random distribution of behaviors: an evolutionary economics (Alchian 1950, Nelson and Winter, 1982, 2002) where selection can operate on more or less randomly generated firms and their behavioral routines. At the other modeling extreme we have omniscient rational choice, where all actual behaviors are hatched being perfectly optimized to the opportunities at hand. In this paper we carve out a realistic role in the middle for the human brain, not just as the usual generator of choices, but as *a virtual selection environment for potential actions* (Campbell, 1974). This intermediate "rationality" acts as a filter between a large (and potentially randomly varied) set of possible action choices, and the much smaller set of actions that can survive simulated evaluations of their worth in the real-world. The pseudo-rational choice that results is fully compatible with our biology and can be expected to produce action choices that might be imperfectly fit to the real environment while perfectly fit to the brain's imperfect representation of that environment.

The details of a specific choice evaluation process will determine when, where and how much slippage might occur, which calls for formal modeling. But rather than creating a new noneconomic or behavioral theory of choice (Simon, 1955), we leverage the existing rational choice framework by finding a realistic and generalized choice model hidden inside. Without slipping out of our economist shoes, we can formalize the theory gap described by Robert Lucas (and admitted by most economists in informal conversation):

"*We use economic theory to calculate how certain variations in the situation are predicted to affect behavior, but these calculations obviously do not reflect or usefully model the adaptive process by which subjects have themselves arrived at the decision rules they use….Technically, I think of economics as studying decision rules that are steady states of some adaptive process, decisions that are found to work over a range of situations and hence are no longer revised appreciably as more experience accumulates*" -- Robert Lucas (1986).

Smith also describes the issue we are trying to address: (2008: p103) *"Equilibrium theory avoided confronting the problem of process…"* We will see how a generalized rational choice model can bring time, ignorance and even entrepreneurship back into the neoclassical framework by fleshing out the rational choice process in a painless and intuitive way.

This paper does not offer new justifications for disregarding known differences between real and rational choice (Friedman, 1953), nor does it add to the collection of experiments that further distinguish real human decision-making from rational choice models and assumptions (Kahneman, 2003, Gigerenzer and Glassmeier, 2011). Instead, my goal is to establish a scientifically sound basis for our existing rational choice framework so that we can eliminate those mismatches and potentially anchor aspects of the behavioral economics research program. This is accomplished by reinterpreting constructivist rational choice models so that they can be compatible with our modern understanding of evolutionary processes (Cziko, 1995). By deriving math from reality and not the other way around, we can formalize a fundamentally ecological rationality that naturally evolves toward the rational choice ideal. We find an evolutionary rationality. The big difference is that this reformulated "rational" choice framework is constructed solely in terms of blind search processes: the same blind variation and selective retention mechanisms that operate throughout nature and have shaped our own biological evolution[2].

Rather than thinking of ecologically rational behaviors as exceptions to constructivist rational choice, we can start to understand traditional rational choice as a special case of (ecologically rational) blind search: when the search happens to be extremely rapid and complete[3]. When this blind search process can take place cognitively, entirely within the brain of a chooser, it even looks like rational choice to an observer. This reformulation also guides us to the important insight that the choice evaluation processes we associate with rational choice will also take place *entirely outside the brain*[4].

We can think of this framework for explicitly modeling choice evaluations as "choice cost economics", in deliberate homage to transaction cost economics (Williamson, 1979). When transaction costs were routinely assumed to be zero, as they were many decades ago, market transactions were by definition unbeatable (Coase, 1960). But when positive transaction costs were incorporated, market transactions lost their automatic theoretical advantage over other forms of organization (Coase, 1937). Nonmarket coordination modes such as firms, contracts and other hierarchical organizations could thereafter be modeled (correctly) as better and cheaper along important dimensions (Williamson, 2010). This paper shows that with positive "choice costs" allowed, rational choice, in the form of mentally simulated choice evaluations, is no longer automatically the best method for evaluating a choice space. Real choice trial costs, choice trial times and choice evaluation accuracies become important empirical variables that define the tradeoffs in allocating blind search trials across alternative choice evaluation methods.

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[2] From the perspective of evolution or "universal selectionism" (Cziko, 1995), trial-and-error processes (aka "guess and check", aka "generate and test") are the only game in town when it comes to explaining puzzles of fit. Divine foresight or miracles are the alternative nonscientific explanations. Campbell (1974) is a uniquely enlightening discussion of the epistemological implications of evolution. Chapter 9 of Cziko Is also very lucid in this regard.

[3] We will see that traditional rational choice really only arises asymptotically, as a corner solution with zero cost and zero time to evaluate each possible choice. It is possible that we have had rational choice thinking backwards for the same reason that evolution was (and still is?) missed in favor of creationist explanations. The fit between behavior choice and environment can be so tight it is hard to believe is not (more) rational. In an interesting twist, many biologists have adopted rational choice models to effectively model animal behavior "as if" they were making rational choices.

[4] This modeling insight can explain many observations of action choices that might appear non-rational or much less rational than they are (heuristics and biases, custom, norms, etc.), as will be discussed later.

In some cases, traditional cognitively simulated action trials will still be the most effective choice method and rational choice will be a good approximation. In others, real action trials may be the best and only option to evaluate choices. In most cases however, efficient search will rely heavily on the neglected *substitutes* for actual choice that exist between purely mental evaluations and actual choice experiences. These substitute trial and error methods turn out to be as ubiquitous and institutionalized in the economy as they are presently ignored in economics. In fact, efficient decision-making may require distributing choice evaluations across *multiple stages of substitute trials*: from very cheap, fast and crude, to more accurate and closer in cost and time to the actual choice trials. For almost every real economic activity there is a choice space that we can model as being actively explored using these methods. We may be limited by our natural origins to blind guesses, but we are able to adapt from bad guesses to extremely good ones, by allocating our guesses efficiently.

This paper is structured as follows. Part One will present some examples to make the ideas above more concrete and to bridge the gap from blind search to traditional rational choice modeling. Part Two will then interpret and generalize our rational choice mathematics to be backward compatible with blind search and introduce some positive "choice cost" concepts. Part Three will provide examples of applying the generalized rational choice model to choice evaluation processes and discuss some implications relative to the standard rational choice model. Part Four will explore how real institutions might fit into the "choice cost" framework with an emphasis on real search spaces, and substitute trial and error methods. Part Five will conclude with a brief summary and some suggestions for future choice cost economics work.

My hope is that the approach herein will be intuitive to (fellow) new institutional economists, who are already proficient in thinking about the bounds on human rationality (Simon, 1956, Conlisk, 1996) and their real-world institutional implications. But the larger goal is to construct a convenient bridge between more dominant neoclassical modeling and more accurate NIE work, thereby tempting some traditional economists with more realistic modeling for minimal extra effort. The better we can formally yet intuitively model rational choice processes and their real choice results, the better we should be able to understand real institutions and their dynamic behavior.

PART ONE: Blind Search and Rational Choice: Two Hands on the Same Elephant

"It would be an error to suppose that the great discoverer seizes at once upon the truth or has any unerring method of divining it. In all probability the errors of the great mind exceed in number those of the less vigorous one. Fertility of imagination and abundance of guesses at truth are among the first requisites of discovery; but the erroneous guesses must be many times as numerous as those which prove well founded." -W. Stanley Jevons (quoted in Campbell, 1974: p. 428)

100 Keys and a Lock

Some intuitive examples can illustrate the abstract ideas discussed above. First, I give you a key ring with 100 randomly ordered keys and a locked door: what is the chance that the first key you choose happens to open the lock?

1/100.

Of course, easy calculation… except I didn't say any of the keys work[5]. Now, having been reminded of the possibility that maybe none of the keys work, you can give a revised answer:

<1/100.

But I didn't say that any of the keys *don't* work either, so the answer could also be >1/100. The real correct answer:

?!

Since any of the keys might work or fail the answer could be any integer percentage from 0% to 100%. There is no knowable "answer" to calculate (just like when you were reading the first sentences of this paper).

Now suppose you actually pick a key and try to open the lock with it. Whether it works or not we can do some Bayesian updating, so supposing it does not work: what is the chance that the next key clockwise to the first one opens the lock?

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It is still a complete unknown[6]. The new answer is not 1/99 for the same reasons that the original answer was not 1/100. We remain in the land of complete ignorance or Knightian uncertainty (Knight, 1921). There are no assumptions about distributions (or about distributions of distributions, and so on) to be made, so a rational answer is not possible[7]. John Maynard Keynes notably described this type of situation: *"About these matters there is no scientific basis*

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[5] Try this yourself on other economists who inevitably answer "1/100" and compare with asking biologists who are likely to respond "how do we know any work?" or entrepreneurs who might say "I don't know, but it sounds like a good start".

[6] Even if we spun the key ring and chose a key at random after trying the first key and updating our priors we still have an undefined answer, just bounded differently: from 1% to 100% if the first one worked and 0% to 99% if it did not.

[7] Genuine ignorance actually reigns at some level for every choice, as noted earlier. If I handed you a combination lock with two dials (0..9, 0..9) and thus 100 combinations and asked the original question you might sensibly assume that one and only one of the combinations works, but that too remains an assumption and not a demonstrated fact. The lock could easily be broken so that no combinations work, or that all work or it could be worn so that neighboring combinations work or just manufactured so that more than one combination works.

on which to form any calculable probability whatever. We simply do not know!" – John Maynard Keynes (1937).

Counting Keys

As you continue your initial trip around the key ring, trying keys, there is no way to know whether the next key will work, not even probabilistically. Only after you have blindly tried all 100 keys in the lock and counted that N of the 100 keys opened the lock, can you calculate a probability, N/100, that a key chosen at random will open the lock[8].

Your answer changed from "?" to "N/100" not because of any changes to the keys on the key ring or the lock, but because you changed by your experience with the blind search results. You adapted from having no mental model of the key ring and lock, to having a model that is functional for probabilistic simulations going forward. This empirically derived mental model is just like the one that you instinctively built, without empirical justification, in answering "1/100" to the original question (if my own mental model correctly assumed you did).

Coloring Keys

Now suppose we take a new ring of 100 randomly ordered keys and a new locked door. You blindly try each of the 100 keys in the real lock, and count them as suggested above to determine that N keys work. But this time, you also have a marker that you use to color every working key with bright red ink.

By counting all the working keys you can build another mental model of randomly trying keys in the lock (N/100). But this time, you can also create a second mental model of trying keys in the lock *individually*, based on their color. You can construct a functional *vicarious* representation of all 100 keys on the ring in which each key is mapped, by color, to its ability to open the lock ("red keys open the lock, non-red keys don't").

Note that even with this new model in place you still have to blindly "try keys in the lock" before choosing one, but now this key trial and error can take place entirely within your mind. Your brain-based simulation can provide exactly the same key evaluation results that you would get from repeating actual trials of all the real red and non-red keys in the real lock, but in a fraction of the time.

[8] Of course even after trying all 100 keys you still might have missed some keys that actually "work" by not jiggling them enough or by trying them upside down and some might have worked only by accident of a temporarily stuck tumbler, but having made the point several times and since we're trying to do economics and not philosophy, we can set aside that deep reality in making the remaining points in this section.

Red Keys

So let us assume that there is at least one red key available on the key ring after the marking exercise above (and we'll also assume that you want to open the lock). When I ask you to pick one of those 100 keys: what is the chance that the first key you choose opens the lock?

100%.

Coloring is certainly helpful... except I didn't say that you get to look at the keys[9].

Yes, you can now perform a flawless mental simulation, vicariously trying keys in the lock in your mind and rapidly determining that you want a red one. But you still need to make the leap from that optimal choice in your head to the actual choice implementation in the real world. Your internal choice of a red key needs to be converted into an external choice of a red key from the ring. This type of intermediate step is typically overlooked because it is so automatic and fast[10].

You don't have to physically try any more keys in the actual lock to find a working (red) key to use, but you still have to externally "try keys in the lock" by "looking at keys to see if they are red". In this case, your visual perception now functions as a *substitute* for the original actual trial and error.

If, as the question (sneakily) allowed, the lights are off or you are wearing a blindfold, you can still do the mental trial and error that lets you "know" that the red keys work. But you won't be able to actually identify a key that works. Without visual search available you are stuck at the N/100 probability of the original example[11]. Then, if I turn on the lights or remove the blindfold, the probability that you choose a key that works jumps to 100%[12]. With your vision working you are able to quickly do substitute visual color trials of all the keys until you find a red one[13].

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[9] We have also assumed that the lock hasn't been reprogrammed or broken so that every key that worked the first time still works with normal jiggling, etc.

[10] You are basically completing a round trip from the real world into your brain and back to the real world, so yes, we skipped over the use of perception in doing the original actual trials for flow of presentation.

[11] We're assuming I didn't switch to a different key ring while you couldn't see, otherwise you would still have to identify the ring itself avoid going from the "N/100" model back to the "?" model.

[12] We're also assuming that I did not use disappearing ink or that the keys weren't all colored red to begin with, etc. If you are growing weary of all the necessary assumptions this section has at least been successful in reinforcing the original epistemological problem, and you have a better appreciation for the Duhem-Quine thesis.

[13] If you forget how many working keys you counted, but remember that red ones worked, you could visually scan the 100 keys with your eyes to count them instead of having to physically try them all in the lock again. This is another example of using your visual perception as a substitute for actual trial and error.

A Quick Recap of the Key Issues

I have briefly tried to illustrate that choice is always and everywhere blind and therefore depends fundamentally on trial and error processes (even if we occasionally delude ourselves to the contrary). This is an unavoidable biological reality. You may have gone from slowly searching through keys in the real world to instantly searching through keys in your head, but at no point have you stopped doing blind search. If you find yourself resisting the notion that choice must be ultimately based on blind search, I invite you to close your eyes for the rest of the day and "rationally" choose your way around your office or home and from one to the other.

Having established the centrality of blind trial and error to real decision-making I have also suggested a basic categorization of trial and error choice evaluation methods for our purposes: *actual* at one extreme, *vicarious* (purely mental) at the other and *substitute* in between. You can always evaluate a choice in the real world by taking the real action: this kind of trial and error is the only way to rise up from our natural baseline of ignorance[14]. But after you have recorded enough external action results you can build a mental model that is functional enough to do probabilistic or even deterministic simulations. Vicarious trial and error in your brain can enable you to evaluate potential choices much faster (and cheaper) than actual trials, as we have seen. Substitute trial and error methods might arise in linking vicarious choices to actual choices and vice versa[15]. Like vicarious trials, these substitute trials are also used to evaluate possible action choices without doing the actions, operating in the large and ignored space between full real world action trials and purely vicarious action trials.

I have adopted the terminology of "vicarious trial and error" (VTE) and "substitute trial and error" (STE) from seminal papers in psychology that first addressed (and distinguished) these concepts.[16] From an economics viewpoint however, the main lesson is that VTE and STE are both *perfect substitutes* for actual trial and error (ATE). All three are methods of blind search, a term we can use interchangeably with "trial and error". As economic substitutes, the prevalence of each and the marginal substitution between them will depend on their different economic attributes such as the cost per trial, time per trial and accuracy of result, as we shall

[14] Even though we may have to start from ignorance we can still have initial unconscious beliefs. Evolutionary psychology argues that we may have evolved "belief" modules (Barkow, Cosmides and Tooby, 1992) and the evolutionary framework used here also suggests that heuristics and biases and emotions generally reflect innate default beliefs that we are born with, similar to the way we are born believing that we will be in a certain climate range making 98.6 degrees Fahrenheit a reasonable body temperature to maintain.

[15] You also needed substitute trial and error to be able to initially build the model that that "red keys work" in your head of course.

[16] I have imported the terminology of "vicarious trial and error" (VTE) from psychology where Muenzinger (1938) apparently coined the term when watching a rat pause to decide which way to turn in a maze. See also (Tolman, 1939, 1948) for VTE and (Campbell, 1956) for STE.

discuss. You might have also noticed that the previous examples show decision-making processes evolving from complete ignorance, to probabilistic uncertainty (risk), to deterministic certainty. These too are familiar concepts from models of choice in economics. We are not quite there yet, but with one more set of examples and concrete concepts, we can complete our journey from biology through psychology back to economics.

10 Keys and 10 Padlocks

Imagine I now give you a key ring with only 10 keys on it, but I give you 10 keyed padlocks. You use a black marker to label each of the keys with a number from 1 to 10 and you also label the locks from 1 to 10. You try all 10 keys in the #1 lock and write down on a piece of paper which key numbers work (if any). You then repeat this for locks #2 to #10, until all 10 keys have been tried in all 10 locks. When you are done you have a list of numbers written on a piece of paper. On each line you have a lock number followed by the list of key numbers (if any) that open that numbered lock.

You have created a complete virtual mapping, on paper, of physical locks to the physical keys that open them[17]. With said paper in hand, actual key trials in the real world are no longer necessary to identify keys that open these locks[18]. You have created *search capital* that can be used in the future to dramatically reduce the time and cost of evaluating the same choices.

Assume that at least one of the keys worked in Lock #7 for example. After you are done recording all the actual key trial results, I might ask you for a key number that opens Lock #7. You could certainly start picking up each of the ten keys and blindly try them in the lock again until you tell me one that works. Or you can do a substitute blind search that is several orders of magnitude faster. You deploy your search capital by looking at the paper to quickly find the key number(s) written on the line for Lock #7 and then read a number to me.

10 Keys and 10 Padlocked Boxes

Finally, imagine that you again have 10 keys on a ring and 10 padlocks, but now each lock is securing a small box that looks like miniature treasure chest. You again label each key 1 to 10 and each box 1 to 10 with your black marker. You try all the keys in all the locks and record the results on paper. However, when a lock is opened you also look inside the box and may find some quantity of dollar bills. After counting any money found inside the box and then placing

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[17] If I then gave you another new lock (Lock #11) to open and asked you which keys, if any, open it, you would have no choice but to take each actual key and blindly try it in the actual lock to answer.

[18] Similarly, if instead you wanted to know which locks a particular key open, you could try that particular key sequentially in every lock. Or the written mapping you already have can be searched for all locks that a particular key opens. It could also be vicariously manipulated into a new, reorganized mapping of keys to the locks they open, again without any physical contact or even looking at any actual keys.

the bills back inside, you put the lock back on the box and record the dollar amount on the line next to the lock number on the paper.

On the paper you have created another virtual mapping of keys to locks that they open. But you have also created a mapping of keys to the money in the boxes secured by those locks. Each key choice is linked on the paper to a total dollar amount.

If I ask you for the key that has the highest "cash value" (equal to its access to dollar bills), you can search through the paper to see which locks are opened by each key. Then you can vicariously add the dollar amounts available from each opened lock and record your virtual manipulation of reality on a new line, all without touching or looking at any keys or boxes. Once you have a list of the total dollar amounts associated with each of the 10 key numbers you can visually sort through the list for the highest dollar amount and then tell me that associated key number.

We have reached the same choice format as rational choice models in economics. We have described an agent with a choice set, consisting of choices (keys), who evaluates the payoff (dollars) linked to each action choice (key number). After he completes an evaluation for each choice, he identifies the choice (key) with the highest value and selects it for action. Key numbers end up mapped directly to cash numbers in this example, just as choices get mapped directly to utility in traditional rational choice models. But now the mapping is derived entirely from doing blind search, all the way down.

Now suppose that unbeknownst to me, you were able to invest the additional time and effort to memorize all the data on the paper, after you wrote it down. You thereby produced another increment of search capital by constructing a purely mental model of which keys opened which locks[19]. When I ask you for the key with the highest cash value, you immediately speak a correct answer to me.

Without handling any keys or even looking at any paper you completed a near instantaneous search in your head to find the best key number. You have not only conformed to the format of rational choice. To an outside observer, your immediate response looks indistinguishable from traditional rational choice.

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[19] Note that the "information" is exactly the same in going from paper to your memory but the incremental investment in "search capital" allows you to blind search that information faster. The decision to create search capital follows the same economic logic as other capital: the value gained from faster speed should outweigh that expended to create it.

From Blind Search to Rational Choice

We have seen how real blind behavior can adapt to approximate "rational choice" as modeled in economics. This fit arises quite naturally when a choice set can be accurately modeled and completely blind searched in your mind. At the maximum speed for this vicarious evaluation, the best choice is immediately identified in comparison to every other choice in the set. At this extreme, vicarious choice evaluation is perfectly instantaneous, costless, complete and accurate, so we have a blind search process that is mathematically identical to rational choice. And vice versa.

Even more interesting is that choice evaluation that is costly, time-consuming, incomplete and inaccurate *also fits into the same rational choice format*. We might be doing actual trials that cost money and take time and therefore have a constraining cost or time budget that limits the extent of our search. And our substitute choice evaluation trials might not be a perfect predictor of the actual choice results[20]. But we can still be in the middle of a perfectly rational *choice process*.

The strong empirical assumption of traditional rational choice is that the best choice result is immediately identified and selected. Our rational choice process only requires the weaker and more plausible empirical requirement that as you work through actual, substitute and vicarious choice evaluations, you continually upgrade your top choice preference to whatever better choices are discovered. With a finite choice set and sufficient time and cost budgets, you have already seen how the two different assumptions might converge on the same actual choice.

Yet from the point of view of traditional rational choice models, these very real "choice costs" *cannot even exist*. Even though real-world choice processes are comprised of blind searches that are known to consume significant time and money, this appears to be a whole area of *economics without any costs*. The situation looks eerily similar to Williamson's brilliantly pithy account of the analysis of transactions, as he found the field in the early 1960s*: "Costlessness abounded, which was bad news for economics*."- Oliver Williamson, 2009 Nobel Lecture

As for the specific opportunity for modeling choice, Conlisk has noted:

"By its most common definition, economics concerns scarcity. Because human reasoning ability is scarce, one could as well argue that economists are by definition required to study bounded rationality."- John Conlisk (1996)

To remedy this deficiency we need to bring choice costs into the standard economic modeling framework. We have traced the steps in nature from blind actual choice trials to a perfect

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[20] It is also true that the results of *actual* trial and error might not be accurately interpretable of course, but hold that thought for now.

mimicry of traditional rational choice models. Now we need to turn around and work our way backward, from the existing equations toward reality. Fortunately, the mathematics of the traditional rational choice model can be generalized in intuitive ways to handle the real choice costs described above. We can use the preexisting implied and explicit logic to complete a transformation from a model of instantaneous rational choice results to one that spans the whole range of real rational choice processes.

PART TWO: Generalizing the Standard Rational Choice Model

"[R]ationality is an assumption that can be modified. Systematic biases, incomplete or incorrect information, poor memory, etc., can be examined with analytical methods based on rationality."
--John Muth (1961)

Revisiting the Standard Rational Choice Model[21]

It is easy to get caught up in the math of making a standard rational choice model (SRCM) and overlook the basic economic logic: an agent is given a set of choices and picks the best one of them. The potential complexities of utility functions, budget constraints, informational assumptions, game trees and so on, are just fancy ways of dressing up the fact that an agent is making a single "best" choice from a choice set with multiple allowed options. While the best choice might not be immediately obvious (or even solvable) from the way such an optimization problem is constructed, it is already defined by the math that may conceal it.

When attempting to model a particular choice situation and payoff environment, we define a set of allowed action choices for one or more agents. Each possible choice is given a payoff score defining which one the agent will like best in different scenarios. A continuous mathematical choice function, $u(x)$ might be used so that one equation can identify the best choice across varying situations, or discrete choices and fixed numbers might be used as in game theory. Each possible choice is an x_i and each choice evaluation yields a u_i as the predicted value for the choice of that action. The SRCM has the agent evaluate the u_i value for every x_i choice and choose the highest value available for $u(x)$. We call this "utility function maximization" (max $u(x_i)$ over $\{x_i\}$), whether the choice set function $u(x_i)$ and domain $\{x_i\}$ are continuous or discrete[22]. The highest valued choice in the agent's allowed choice set is always identified and selected by the modeled agent in the SRCM.

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[21] My use of the term "standard rational choice model" or "SRCM" is similar to the phrase "standard social science model" or "SSSM" as used by Smith (2008) but may not be identical.

[22] If equations are used, additional mathematical assumptions are invoked for convenience in doing analytical maximization or minimization (convex/concave, single-peaked, no discontinuities, etc). These just serve the function of automatically making all choices inferior by definition to the one identified analytically.

We can do this kind of modeling in our sleep, but perhaps that is why we might not have noticed several critical but *implicit empirical assumptions* built into every SRCM that matches the description above.

1: The agent's evaluation of $u(x_i)$ values for each x_i is *instantaneous and costless*

2: The agent's evaluation of $u(x_i)$ values for each x_i is *exhaustive* to include every x_i in the choice set $\{x_i\}$

3: Each ex ante modeled expected payoff $u(x_i)$ *exactly matches the actual ex post payoff result* for each x_i

We can look at each of these three implicit assumptions in turn and intuitively generalize them by making them explicit. Once we attach some explicit economic parameters to these implicit assumptions we can understand when the SRCM is a good fit to reality and when it is not. While we are then forced to explicitly and publicly acknowledge the conditions under which our beloved SRCM turns out to be a poor model, we can use a generalized alternative to continue our proud march under the flag of economics[23].

SRCM Assumption 1 Made Explicit: Instantaneous and Costless Choice Evaluation

First, consider the instantaneous and costless evaluation of $u(x_i)$ values for each choice in $\{x_i\}$. From the examples of using real keys to open real locks, we can see why this is unlikely to be a realistic empirical assumption. In the real world we know that each $u(x_i)$ "calculation" is a blind evaluation of a choice (x_i) that might be performed by any method along the spectrum from vicarious choice trials to actual choice trials. So why don't we just assign an explicit "time to evaluate" (t_i) and explicit "cost to evaluate" (c_i) to each choice (x_i) in the modeled choice set?

The appropriate costs and times to use will vary depending on the specific choice evaluation method being used, but all real choice evaluation takes measurable processing time even if it is sub-second mental deliberation[24]. Many choice evaluations will also cost money, so for each choice x_i, an empirically realistic choice model should have a time, t_i, and a cost, c_i, as potentially nonzero variables. These are easily populated with empirical facts from the real world example being modeled.

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[23] In fact, the generalized version of the SRCM might allow us to extend the reach of the rational choice paradigm into remaining holdout areas of social science… Yes, I'm looking at you, sociology.

[24] While real vicarious choice may rewire under a second for complete deliberation if the average neurons take milliseconds to fire (Montague, 2006), your brain might be glacially slow compared to the nanoseconds it might take for a computer to do the same vicarious task. Thus we might expect the computer to be earn a lot of blind search work.

In the SRCM, each $u(x_i)$ choice evaluation is implicitly assumed to run instantaneously (and for free) on the agent's existing mental model, which may or may not be a decent approximation to reality. A compelling mathematical feature of the inclusion of the t_i and c_i variables is that as $\{t_i\} \rightarrow 0$ and $\{c_i\} \rightarrow 0$, we have asymptotic simplification back to the SRCM. Our new explicit cost and time structure can still model $u(x_i)$ evaluations that take place instantly in the brain as traditionally modeled, or that can consume significant time and/or cost.

The more profound consequence is that this one extension expands the formal rational choice framework beyond just modeling internal deliberation processes. Our conception of rational choice can now include *external choice trials* in the real world that also have nonzero times and costs, such as trying keys in a lock or looking through labeled keys. These real-time, real-world processes can be understood as a form of "external deliberation": a rational choice process of search through a choice set that takes place outside of the human mind[25].

SRCM Assumption 2 Made Explicit: Exhaustive Choice Evaluation

Next we can look at the implied assumption of e*xhaustive* evaluation of every choice in the choice set $\{x_i\}$. With zero time and cost to evaluate each choice x_i, the whole choice set always gets completely evaluated in an instant. But with nonzero times and/or costs to evaluate each choice, we can see how a finite time or cost budget for a choice problem might lead to some choices not being evaluated[26]. So why don't we make a mathematical distinction between the choices included in the allowable choice set that *are evaluated* by the agent $\{x_i\}$, and whatever choices are included in the allowed choice set but *are not evaluated* $\{x_i'\}$?

The set $\{x_i\}$ is now explicitly a *consideration set*[27], a subset of the larger feasible choice set that is actually evaluated (considered) by the agent. We have also extended the SRCM to incorporate an explicit form of bounded rationality: *bounded deliberation*[28]. We retain the desired result that as $\{t_i\} \rightarrow 0$ and $\{c_i\} \rightarrow 0$, we necessarily have $\{x_i'\} \rightarrow \{\}$, and the generalized model simplifies to the SRCM. Also, if there are a small number of allowed choices in the choice set and/or the times and costs for each choice evaluation are small relative to a total time budget, T, and cost budget, C, ($\Sigma t_i < T$ and $\Sigma c_i < C$), then we might still expect $\{x_i'\} \rightarrow \{\}$ because all the choices can be evaluated.

[25] The term "deliberation costs" (Conlisk, 1996, Spears, 2009) has been usefully applied to the costs of thinking through potential choices in your mind. The implications of "external deliberation" are explored in Part Three.

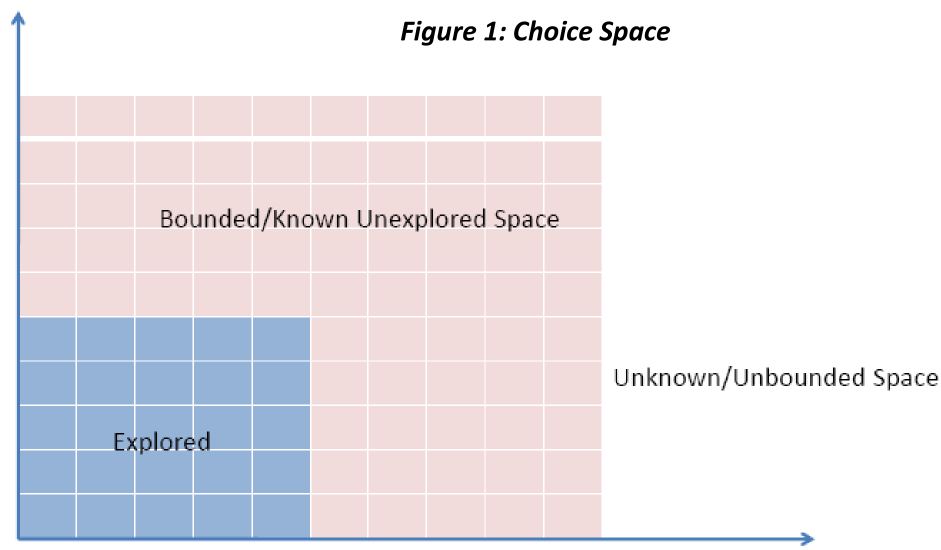
[26] The classic recognition of the fact that large but finite choice sets may not be fully explored is the choice set of chess game strategies (Simon, 1955). Formalizing bounded rationality in a way that economists can easily digest appreciate is a subgoal of this paper.

[27] The term is borrowed from marketing literature where it first arose as from thinking about the limited subset of brands that real consumers actually consider (Howard and Scheth, 1969).

[28] Knudsen and Levinthal (2007) note that the choice set evaluation aspects of bounded rationality have been largely ignored, at the expense of choice set creation, in behavioral models of learning.

Note that even when all the choices inside the choice set have been evaluated, there will always be infinite choices that are not evaluated because they were explicitly (or implicitly) modeled as outside the choice set and therefore not allowed to be evaluated or selected (Figure 1). Thus, for the sake of completeness, we can at least acknowledge a set of other conceivable choices { x_i} which end up explicitly modeled as outside an agent's modeled choice set {{x_i},{x_i'}}, presumably but not necessarily because they are worse than the choices included inside the choice set[29]. A model of the choice of keys key on Ring A necessarily excludes the choice of any key on Ring B. More subtle is that modeling a decision to search through actual keys to open a lock implicitly excludes the conceivable choice to break the lock open with a drill or a bolt cutter[30].

Figure 1: Choice Space



We can also see that even so-called "rational choice" models are intrinsically *bounded* rationality models because there are always some possible choices that are implicitly or explicitly excluded from mathematically modeled choice sets. This does not depend on nonzero cost and times to deliberate. All rational choice set models operate on choice set models that are arbitrarily smaller (more bounded) than an alternative choice set that could have been used. Thus, what we currently call rational choice is just another simplified decision-making

[29] Making this recognition explicit can create insurmountable problems for rational choice models of "inefficiency" (Lyons 1996, 2010)

[30] One example of explicitly excluded choices is product purchases which may be disallowed within the problem environment in the face of a budget constraint. The most interesting examples (and historically important modeling errors) are choices that were categorically excluded from standard models by implicit construction (lack of opportunistic choices, lack of choice over institutions, etc).

heuristic because of the artificially limited number of choices and choice dimensions over which "rational choice" is allowed to operate[31].

It is also worth noting that being explicit about bounds on choice sets and consideration allows us to rediscover creativity and *entrepreneurship* within the neoclassical framework. Entrepreneurs invent new choices, some of which they then might develop and offer to other people. The creativity step can be formally modeled as the creation of new choice set elements in an agent's own choice set. Entrepreneurship can be formally modeled as the creation of new choice set elements in other agent's choice sets.

SRCM Assumption 3 Made Explicit: Choice Evaluation Predictions Match Choice Results

"An individual's reality model can be right or wrong, complete or incomplete. As a rule it will be both incomplete and wrong, and one would do well to keep that probability in mind."-Dietrich Dorner (1996)

Having addressed the matter of choice evaluation we can now consider what happens with the choice evaluation results that are obtained from that process. The SRCM assumption is that the choice payoff results obtained from the evaluation process will exactly match the real action payoffs (or distribution of payoffs) observed when those actual choices are made. In other words, you may have evaluated a set of choices and then picked the one that appeared best, but the payoff you actually get from that action choice might turn out to be different from what you expected[32]. If the error is large enough ex post it is possible that in hindsight you would have made a different ex ante choice. So why don't we explicitly recognize that an agent's ex ante subjective mental model of expected choice set payoffs, $u(x_i)$, might be different from the actual ex post payoffs?

We can specify an "actual payoff" function, $a(x_i)$, that contains the actual payoffs from making each choice x_i in the real economy, as opposed to the $u(x_i)$ from your own prior evaluation of choices. The function $a(x)$ is essentially an objectively true utility function, which the SRCM implicitly assumes is the same as the subjective utility function $u(x)$. In other words, the SRCM assumes that the agent's internal model of reality is a perfect representation of the external world. This is certainly a possible endpoint as the subjective $u(x)$ function evolves and adapts to match the objective $a(x)$ function over time. But empirically this means a point is reached after

[31] This is why "irrational" strategies can be generally better than arbitrarily defined "rationality" (Waksberg et. al. 2009). In economics, for example, we know that rational "profit maximization" can be inferior to other strategies in terms of economic survival (Radner, 1998). And other heuristics can not only be faster and simpler than their rational choice substitutes, they can also outperform them (Gigerenzer & Glassmeier, 2011).

[32] Over 50 years Herbert Simon made a plea for "*the necessity for careful distinctions between subjective rationality, and objective rationality…To predict how economic man will behave we need to know not only that he is rational, but also how he perceives the world- what alternatives he sees, and what consequences he attaches to them*…" (Simon,1956, pp271-272). We would like to enable this formal distinction between subjective and objective rationality within the rational choice framework.

which there can never be any surprises. More realistically, for each choice x_i in the choice set, we might want to allow for a simple surprise or error function $e(x_i)= [a(x_i)-u(x_i)]$ or a formula for the percentage error relative to the actual result, $e(x_i)/a(x_i)$[33]. In either case, positive errors are good surprises and negative errors are bad surprises.

In many real examples there will no empirical reason for an agent to have developed an accurate mental model of particular choice outcomes[34]. In these cases we have $u_i \neq a_i$ for a given x_i, or for some subset of choices, or for the whole choice set $\{x_i\}$. For many other real choices an agent might not have any meaningful mental model for the outcomes of choices at all. As we have seen with the lock and keys examples, there is no baseline for surprise when blindly trying keys for the first time. Quite generally, an agent might try an action in the real world hoping for a good outcome, but without any concrete prediction of what will actually happen. Thus we can recognize that $u(x_i)$ might be initially *undefined* for a given x_i even though $a(x_i)$ might be perfectly well defined in an objective sense (to some more knowledgeable observer) for the same x_i in the model. Leaving a u_i value null, $u_i = \{\}$, can represent complete ignorance, where the actor has no meaningful vicarious model or prediction of what will happen prior to an actual choice. These are the cases where doing a substitute or actual choice trial in the real world becomes the *only* way to evaluate that choice and thereby initialize that u(x) value.

As with the previous two extensions, making this third assumption explicit still allows for simplification to the SRCM. When there is no difference between vicariously evaluated choice results and actual outcomes, $u(x) \rightarrow a(x)$ and we arrive back at the SRCM. This will necessarily be the case as $\{t_i\}\rightarrow 0$ and $\{c_i\}\rightarrow 0$ for evaluating actual choices since the choice set could be fully evaluated by just trying actual choices. Equivalently, we can think of $e(x) \rightarrow 0$ as $\{t_i\}\rightarrow 0$ and $\{c_i\}\rightarrow 0$ after actual choice results, $a(x_i)$, have been used to create an accurate mental model, $u(x_i)$, that can then be instantly and costlessly searched for the same choice problem in the future[35].

Rational Choice Results versus Rational Choice Processes

We now have a formal yet simple "generalized" rational choice model (GRCM). Given the same choice set, and time and money for enough trials, we have seen that the GRCM and SRCM will yield the same optimal choice in the choice set. The GRCM is like a slow motion version of the

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[33] The idea is in the same spirit but functionally different from Shackle's surprise function (Shackle, 1949).

[34] Actual choice experiments are the only option when our mental models are not developed enough for unambiguous simulations. As my old chemical physics advisor liked to tell us in our lab: "Why don't you stop the debate and just run the damn experiment",

[35] We are assuming an time-invariant actual environment of course but by allowing surprise we do open the door to modeling environments that vary In unpredictable ways to the agent.

SRCM with a messy real-time choice evaluation process that we can watch. In the SRCM that process is just too fast to allow us to observe anything other than the rational choice result.

Both models rely on the same core "rational comparison" mechanism that requires that agents to climb up a ladder of utilities and never intentionally down[36]. The difference is that the SRCM requires that the agents always reach the top of the ladder and the GRCM does not. In other words, from the GRCM perspective, observable choice errors are only superficial evidence of less than fully "rational" behavior: they could just be from a snapshot in the middle of a real-time rational choice process. Empirically, this rational comparison assumption translates to a weaker, procedural form of rationality that is easily satisfied in the real world.

Combined with the newly variable assumptions, the GRCM becomes a much better fit to human choice processes. Our GRCM still has the SRCM surviving inside it as a special case, both theoretically and empirically, but the GRCM fits to situations where we may or may not observe rational choice results or any equilibrium at all. We have created a way to bring real time and ignorance, and thus disequilibrium, back into neoclassical economics through the simple logic of real-time choice evaluation processes. As Knight once noted: *"It is evident that the rational thing to do is to be irrational, where deliberation and estimation cost more than they are worth".* -Frank Knight, 1921

We now have the basic elements of a "choice cost economics" framework: cost per blind search, time per blind search, completeness of the blind search process, and predictive accuracy of the blind search results. While not a complete generalization, the following examples illustrate how this basic GRCM opens some new modeling possibilities by allowing important realities that the SRCM assumes away.

Implications of the GRCM versus the SRCM: A Combination Lock and a Treasure Chest

Suppose I have a numerical combination lock with two dials that each spin from 0 to 9, thus offering 100 possible combinations from (0,0) to (9,9). I use the lock to secure a treasure chest filled with $100 which I hand it to you with the instructions that you can have the money inside if you can open it. I also tell you I'm only giving you a fixed period of time before I take the chest back. You rationally seek to open the lock as soon as I hand it to you.

[36] This simple "rational comparison mechanism" by blind trial and error might even meet Simon's description of *"…the kind of economic theory that we should all be seeking: a theory that describes real-world phenomena and begins to unify the description by the demonstration that a relatively small number of mechanisms (combined with a large body of knowledge about initial and boundary conditions) can produce all or most of these phenomena — not all of the phenomena that we can imagine, but those that actually occur."* –Herbert Simon (quoted on p190 of Rubenstein, 1998). Trial and error is the only general purpose problem solving method we have as Simon would attest if alive today.

The SRCM implicitly yields an immediate "equilibrium" state where you have the lock open and the $100. Where you start, how you proceed and whether you have any help are all irrelevant to achieving this equilibrium outcome. The SRCM implies a situation where you can somehow turn and test each actual combination in maybe a millisecond, thereby sequentially completing all 100 combinations in 0.1 seconds and guaranteeing that the lock is opened before I could even ask for the chest back. More realistically, the SRCM accurately describes the case where you realize you have previously opened that same lock. It is then possible to find the correct working combination in your mental model in 0.1 seconds, thereby opening the lock on your first action trial. These numbers are just an arbitrary fit of the SRCM to reality of course. The same SRCM equilibrium would necessarily result if the lock had 1000 combinations or even 10^{1000} combinations, and even if there were 1000 (or 10^{1000}) other locks on the same chest.

With the GRCM, we can model actual trials of different combinations by plugging in real nonzero empirical data and exploring the implications. Figure that it takes about 6 seconds to accurately select and evaluate each new combination, allowing 10 combinations per minute and 100 combinations in 10 minutes. Suppose the working combination is (4,9).

Time (or Cost) Budget: Stopping Point Matters

With the SRCM, choice evaluations are instantaneous so you open the lock and get the $100 regardless of whether I give you one second or one day. With the GRCM we change $\{t_i\} = 0$ to the realistic constant $t_i = t = 6$ seconds for each actual combination trial. Then we model an initially ignorant agent, $u(x)=\{\}$, going through the full choice set of 100 actual combinations in real time. If the time budget for getting the lock open is greater than 10 minutes (600 seconds) the result will be a fully evaluated choice set with $\{x_i'\} \rightarrow \{\}$ and an open lock[37]. The $u(x_i)$ values end up fully populated with accurate $a(x_i)$ data just as the SRCM requires.

However, if the time budget for choice evaluation is 6 seconds, only one combination can be evaluated, leaving $\{x_i'\}$ containing 99 unevaluated combinations with $u(x_i)=\{\}$ for each of them. When I reclaim the chest, I am almost certain to observe that you have chosen an "irrational" combination that doesn't work. The (generalized) rational choice result is that the lock is unopened and you do not collect $100.

Initial Conditions: First Guesses (Initial Biases) Matter

With the SRCM, instantaneous choice evaluation means exhaustive choice evaluation, so it doesn't matter in what order you evaluate choices. In the GRCM, initial conditions cannot be

[37] We are assuming the use of any search path through the combination space without repetition. Note that without constant t=6 values (or with constant t per dial increment) we might be restricted to a sequential search path that minimizes step times (the time-consuming turns of the combination dials) to the smallest (one) increment at a time: either a sequence like (0,1), (0,2) (0,3).. (9,9) or (0,1), (1, 1), (2, 1) … (9,9).

ignored. Suppose you think you recognize the lock as one that you once opened with the combination (5,0). You make your first actual trial (5,0) and when it fails you start dialing sequentially through (5,1), (5,2) and so on until your 100th guess of (4,9) opens the lock. Your initial subjectively rational belief was that u(5,0) had the highest value and would open the lock. This was based on the perceived fit of the choice problem to a previously constructed mental model. In reality, this previously constructed belief caused you to perform much worse than randomly expected in terms of total time to open the lock.

This is an example of how we might expect to observe "bias" effects, relative to the predicted SRCM results, if the implicit SRCM assumptions do not apply. We might observe actions that are really just early action trial guesses and not the final adapted results of a complete choice evaluation process. In the SRCM the starting point is irrelevant because all combinations are evaluated. In the GRCM, we might expect convergence to the SRCM after some number of steps, but the process we observe may not run that long. We should generally expect first guesses (preexisting mental model beliefs) to affect observed action outcomes whenever the rational choice process is stopped prior to complete search and thus prior to u(x) ➔a(x).

Path Dependence: Sequence Beliefs Matter

For the same reasons that the starting point can be important in GRCM and irrelevant in SRCM, the sequence of choice evaluations can also matter to observed rational choice "results". Suppose I give you the lock, set initially to (3,0). You might guess (correctly) that I was lazy and failed to move the dials much away from the actual combination. If you start with (3,0) and explore the four combinations on either side of (3,0) you will cover (2,1), (4,1), (2,9), (4,9) and have the lock open within 4 additional steps. You might guess instead that I placed the dials as far away as possible from the working combination. If you end up starting there at (8,5) and exploring around that combination, you might take up to 100 steps to make your way to (4,9). None of these hunches or beliefs as to what sequences you should follow matter if you have more than 600 seconds. But if you have less than 600 seconds to open the lock, any of them could affect whether you get the lock open and the $100.

Feedback Quality: Accuracy of Choice Evaluation Results Matter

Result accuracy is a larger topic than we can cover in any depth in this introductory paper but it can be important in real choice and is another potentially important generalization of the SRCM. When you are trying actual combinations, you could initially pull on the lock and find that it stays closed. Then with a bit of jiggling on the same combination the lock might actually open, revealing that you did have the correct combination. Every choice evaluation, whether vicarious substitute or actual, could be modeled as having some objective probability of returning an incorrect result, which means that an agent's subjective u(x) model could be different from the objective a(x) model even *after* an actual choice evaluation[38]. With enough trials this could stabilize into a probabilistically predictable expected payoff if the randomly contributing factors persist, or a deterministic result might emerge, as with always jiggling the combination lock to test combinations.

SRCM (Constructive) Rationality and GRCM (Ecological) Irrationality

There has been a tension between behavioral economics experiments to catalog biases and the SRCM theoretical program of assuming them away. The GRCM examples we just covered show why there need not be contradictions in going from one view to the other. The behavioral economics program can be seen as developing *positive theories of first guesses* and adaptation paths. This is critical data for the GRCM. In contrast, the SRCM theorists have developed idealized theories of fully adapted "last guesses" for which initial conditions and paths do not matter by construction. Both approaches still use the same core mechanisms of a rational choice process but different process details can generate different empirical predictions.

"Irrational" choices are certainly expected to be observable in the real world for the same reasons we see wrong answers on multiple choice tests: only one guess can be recorded as the observed answer[39]. Depending on the number of choice evaluations required to actually travel from first guess to final guess, and the many other details of how a choice problem is actually perceived and experienced relative to the modeled assumptions, there may or may not be observed convergence in typical experiments with action guesses matching SRCM results[40].

Many real choice problems have significant choice evaluation times, costs per evaluation, large choice spaces and variable evaluation results that can make it unreasonable to expect real action choices to converge to predicted SRCM results. The bigger a choice set is, or the slower and costlier to do choice evaluations accurately, the further away from SRCM we have to expect to find action choices in the real world.

This section has developed a GRCM framework, fixing assumptions that can prevent the SRCM from being a good match to real human decision-making processes. We have also highlighted some new challenges to optimal action choice that arise in that world according to GRCM. Fortunately, the next section describes real examples of GRCM-compatible solutions that can make optimal SRCM-like behavior much more likely in the real world. These include ways of

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[38] We described a case where we might have come away believing that a choice was worse than it actually was when it was actually better, but the opposite is also valid through some unknown fortuitous coincidence that contributed to a higher payoff but will not be there in the future. We might even expect substitute choice trials to produce these Type 1 and Type 2 errors as a tradeoff for their speed and lower costs.
[39] Just imagine if you got 4 guesses at each A, B, C or D question. (Or if choices A, B, C, and D were followed by "E: None or more of the above"). You could get 100% on any such multiple choice test in any field.
[40] And as discussed earlier, the "rational" model may not be actually as good as alternative strategies.

shrinking real choice sets, accelerating their complete evaluation and lowering the baseline costs and times to evaluate actual choices by use of substitutes for actual choice trials. From the perspective of the choosing agent, these substitute choice evaluations can include using the results of prior choice evaluations performed by other agents.

PART THREE: Choice Evaluation in the GRCM

We noted earlier that one implication of recognizing positive "choice costs" is that the human mind no longer has an insurmountable competitive advantage in its ability to do choice evaluation. The "rational" calculation of optimal potential actions within a single mind might be more efficiently accomplished with faster, cheaper or more accurate processes for choice evaluation that operate *outside that mind.* This implication becomes a key to mitigating the effects of positive choice costs when we also consider that a single mind no longer has a built-in advantage over *multiple* minds, or over multiple people doing actual choice evaluations. The GRCM supports the modeling of the full range of economic substitutes for choice evaluation that include these options, ranging from 100% vicarious trials of choices in the mind, to 100% actual choice trials in the real world. The substitute methods between these endpoints can be combined with algorithmic strategies for efficiently evaluating choice sets. These approaches help GRCM-compatible blind choice evaluation evolve quickly and efficiently toward well-adapted, SRCM-approximating results.

Parallel Search: Help Matters

Suppose that I now have two identical 100 digit combination locks, including one that I attach to the chest that I give you with $100 inside. The other one I give to a friend of yours who sits next to you. I then give you 5 minutes (time for 50 combination attempts) to open the chest. Do you succeed?

It depends. In the SRCM you always succeed on your own, so help is unnecessary, but in the GRCM, search assistance can be very valuable. Your friend can be working on the same lock at the same time in a *parallel search* with you. If he finds the working combination before you do, he can immediately communicate it to you, for use as your own next action trial. If you both spend your allotted time trying different combinations at random, you will inevitably cover a larger region of combination space than you would have on your own, but you might not succeed in opening the lock within 5 minutes. However, if you coordinate an *efficient parallel search* you are guaranteed success. You can split the 100 combinations into two non-overlapping batches of 50 combinations that you each work on at the same time. You will have all 100 combinations tried in 5 minutes, guaranteeing success in half the maximum time as before.

Parallel search is a concept that is pointless in the SRCM but goes to the core of how the real world actually functions[41]. Real searches might be performed by a handful of people or by millions operating in parallel throughout the economy. Coordinated parallel search with communication can dramatically accelerate the total time to do choice evaluation even though it does not shrink the choice set at all[42]. If I have 100 identical locks instead of just two, and give them to you and 99 assistants, you can find the working combination as a (communicating) group after one 6 second step with one trial per person. Together, the 100 mental models form a complete model of the combination lock that you can use as a substitute for trying all the numbers on your lock yourself[43]. As soon as the successful combination is announced by whoever finds it, you can set it on your own lock as the next trial and have the lock open in 12 seconds. Even though everyone is still doing slow actual trials, the total time to optimally solve the choice problem is within 12 seconds of as fast as it could be. Thus, sufficiently parallelized search can accelerate choice set evaluation to the point that observed results end up close to the prediction of the SRCM, even for large search spaces[44].

Modular Search: Decomposability Matters

The gains from parallelization are impressive, but small compared to the gains from modularization. The ability to separate the choice set into modular subsets can dramatically shrink the total number of choices that need to be independently evaluated. Suppose I put a new lock on the chest that has 10 dials for a total of 1 billion combinations. At 6 seconds per combination it would take you up to 6 billion seconds or just over 190 years to discover the 10 digit combination. Even if you had help from assistants with 99 other identical locks it would still take up to 1.9 years before you could guarantee you would achieve the SRCM result.

But suppose instead that the same 10 combination dials were spread over 2 locks (attached to the same latch) with 5 digits and 100,000 combinations each. It would now take you up to 600,000 seconds per lock (just under 7 days) to try every combination. Both locks and the chest would be open within 14 days instead of 190 years[45]. In the limiting case you can imagine the 10 combination dials spread across 10 locks so that each of the ten dials is its own combination lock with just 10 options. Working all by yourself you would have the first lock open in no more

[41] There appears to be almost no work on parallel search in economics, with Nelson (1961) and Vishwanath (1988, 1992) as notable exceptions. Also see Boudreau et. al.(2008) for applying parallel search ideas to organization.

[42] The total cost of evaluating the choice set remains unchanged since you still do (and pay for) every trial.

[43] Efficient parallel search shrinks search times by 1/N where N is the total number of searchers. The same search that takes 1 unit of time with one search takes 1/N units of time with N searchers in parallel. Note the comforting economics in that there are diminishing returns to adding each additional searcher. For an overview of parallel algorithms in computing, where their study is a vibrant field, see (Xavier and Iyengar 1998).

[44] An interesting recent example of parallel search was the parallel allocation of Google Earth satellite image data to volunteers to help visually search for a lost aircraft (Steve Fossett's) in and around the Sierra Nevada mountains. The effort did not find the plane they were looking for did find the wreckage of several other long lost aircraft.

[45] Modularity has been notably discussed in problem solving by Simon (1962) and in evolution by Dawkins (1986).

than 60 seconds and have all 10 locks open within 10 minutes. You find the exact same 10 digits within 10 minutes of fully modularized search as you would in 190 years working with a single 10-digit combination.

If a similar choice has ten different characteristics (a consumer product for example), modularity gives you the ability to evaluate the set for each choice characteristic independently. The total time and cost savings can be exponential whenever this choice evaluation strategy can be implemented.

Substitute Actual Experience: Prior Choice Evaluations Matter

Clearly you can build your u(x) model through your own actual choice evaluation results, ideally using an algorithm for parallel or modular search, or both. Even more useful is being able to rely on the past experience of people that have already evaluated the same choices in the same choice environment. If an actual choice set evaluation result has already been done and communicated there might be no need for anyone to do it again.

Suppose I secure the chest with ten locks that each have 10 digits each. Or suppose the chest only has one lock on it, with only 100 combinations, but it takes 19 years to find out if a single combination works. In either case, opening the chest could take up to 1900 years so you are extremely unlikely to find a solution by yourself during your lifetime. Even with help you are not getting the chest open on any time scale approximating the SRCM. In the first case, efficiently parallelizing the 10 locks across 10 people would cut the maximum time to 190 years. In the second case, assigning each of 100 people a single combination would still take 19 years to complete. If you want the lock open any time soon you would appear to be stuck. Unless someone else previously figured out the combination(s) you need.

The earlier example of 100 parallel combinations could have been an example of using other people's previous experience as a substitute for your own trials, if only the other 99 people had done their parallel combination trials before you arrived on the scene. It could also have been one person doing 100 trials sequentially, long ago. As long as the past choice evaluation results can be accurately communicated to you through time to the present, the mix of serial and parallel is irrelevant. All that matters is that the necessary choice evaluations have already been done and recorded by someone in a way you can use.

In this case, there might have been anything between 100 trials performed in parallel 19 years ago and a serial sequence started at least 1900 years ago. You can quickly search the historical results of these actual trials as a substitute for accumulating new actual experience, and quickly find the optimal choice within the set of previously evaluated choices[46].

The usual way to summarize this kind of broad experience with previous choice evaluations is by *theories*. When applied to the same vicarious choice problem they can dramatically shrink the size of the remaining choice set that needs to be evaluated[47]. Good theories vicariously rule out large regions of inferior choice space correctly, so that a much smaller number of actual choices (perhaps only one) need be tried to identify the best one in the whole set[48]. Recipes, instruction manuals, blueprints, designs and other how-to guides are strings of single choice action steps that act as theory, suggesting a specific sequence of behaviors within an enormous space of possible actions. A straightforward search through explicit directions can substitute for the often hopeless task of starting from scratch and searching an actual choice space ourselves[49].

Substitute Choice Trials: Lower Choice Evaluation Times and Costs Matter

We have so far focused in this section on full cost and time actual trials to evaluate choice results. We saw how the results from contemporaries or historical assistants doing actual trials could substitute for yours, but everyone was still doing actual trials. Now we can turn briefly to how agents might do substitute choice evaluations on their own.

Suppose we return to our key ring with 100 keys and a lock. If I showed you an actual key ring it might have keys with different shapes and embossed labels such as Schlage, Kwikset, Yale, Ford, Honda and Toyota. I might then show you the lock, which happens to be labeled Schlage[50]. You could start working your way around the entire ring, one key a time as before, ignoring the labels and physically trying each key in the lock. Or you could start working your way around the key ring, skipping over every key not labeled Schlage and only physically trying

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[46] You can think of scientific research and software development as fitting this example pretty well.

[47] Isaac Newton once sung the virtues of vicarious cumulative search: "If I have seen a little further it is by standing on the shoulders of Giants." Imagine aiming a mortar for the first time without having Newton's equations to calculate the settings for a first shot. In fact, real mortar operators use Newton's theory for their first guess and then trial and error adjustment from there based on where the first shot actually impacts relative to the target.

[48] A simple example is using a quick analytical manipulation to solve an algebraic equation versus blind guess and check with random number guesses until you discover a working result.

[49] This is why modern Americans might perish when stranded in regions that Inuit thrive in. Simple warm clothing design spaces are far too big to rationally explore in a lifetime, nevermind the days or hours you have before you get frostbite out in the elements in Northern Alaska. For example past Inuit (modular) search through "boot space" for shell materials, stitching materials and stitching method seems to have led to a sufficiently warm and waterproof seam solution around a thousand years ago that has been passed on to survive today in their culture (Richerson, 2011). Good luck rediscovering that on your own.

[50] If you already miss the combination locks, pretend I'm showing you 2, 3 and 4 digit combinations and a two digit lock.

the Schlage keys[51]. You use your vision to do the substitute search that rules out all the Kwikset and Yale and other keys[52]. As long as this substitute choice characteristic correlates with the actual choice result, you can usefully do much faster and cheaper trials for most of the choice set to rule out choice set elements. Without subjecting them to actual trials you can eliminate certain choices yourself and thereby form a smaller choice set for the next stage. This next stage of choice evaluations could be actual trials, as with the Schlage keys, or another stage of substitute trials.

Some Economics of Substitute Choice Evaluation Trials

If the predictive accuracies of different substitute choice evaluation methods are the same, the ones with the lowest cost or time per trial are used, depending on the cost and time tradeoffs and constraints. This economic logic also suggests that over a range of predictive accuracies, lower cost and faster choice evaluations will be correlated with lower predictive accuracies[53]. The time and cost of substitute choice evaluations will be bounded by zero time/cost/accuracy at one extreme and by the time, cost and accuracy of actual trials at the other[54]. Any substitute trials that cost more, take longer and are less accurate than actual trials, would not be observed, since they make no economic sense relative to just doing actual trials[55].

No Search: Habit

We have held up the SRCM approximation as the gold standard for completing an entire choice set evaluation in a short period of time. Thus we have shown ways to lower the total time and cost to evaluate a real choice set. But there is actually something thing better than a really fast and cheap search through a manageable choice set: no search at all.

Imagine you find yourself confronted with the same combination lock, with the same combination, over and over again as a choice environment. After the first set of actual trials that open the lock, you might build a vicarious model of the combinations that do not work and the one that does. But where there are nonzero costs or times to search (as there are even in your own head), and where the answer is not changing, why even repeat the vicarious search at all? Indeed, we might expect to see certain action “choices” become directly and unconsciously linked to choice situations that are unchanging. This allows for an automatic “choice” of action without any deliberation or other choice evaluation. More precisely, a theoretical belief forms

[51] This is implicitly a test of your “Schlage lock theory”, which you might reconsider if none of the Schlage keys work and you definitely reconsider if one of the non-Schlage keys does.
[52] Our vision and other perceptions evolved to be general substitutes for actual trial and error (Campbell, 1956)
[53] This is analogous to probabilistic search strategies with costs (Stone, 1989).
[54] Vicarious mental search might appear to be the fastest form of substitute search but computers would argue otherwise. For an early investigation of the possibilities for complex computer simulations see Casti (1997)
[55] This assumes error costs are the same: “crashing” with a $100/hour flight simulator might be a much better deal than crashing an $80/hour actual airplane rental.

that shrinks the choice set for a given choice environment to only one element. That choice is thereafter automatically selected in that choice environment without any search delay. We no longer have “choice”, we have habit or routine or even instinct.

Any past search through actions, completed for an unchanging problem, might lead to a specific response that becomes more or less hard-wired[56]. Of course, when these relatively fixed choice rules meet a slightly (or very) changed choice situation, this hard wiring can lead to “irrational” behavioral anomalies or bad habits[57]. Somewhat ironically however, when this ostensibly non-rational behavior takes place in its proper choice environment, it comes as close as empirically possible to fitting the implicit assumptions of the SRCM[58].

No Search: Norms (Parallel Habit Copying) and Custom (Habits Transmitted Through Time)

There are other forms of mindless “choice” to consider. What if we could watch the actions of other people who are already behaving in the same choice environment, then just copy their observed action choices? Copying a habit from someone else is even easier than developing your own. Mindlessly copying and following someone else’s decision rule is like mindlessly following your own decision rule, but also saves you your own actual trials. For the same reasons it makes sense to adopt a habit from our own actual experience, it can make sense to adopt a habit from someone who already has actual experience in a particular choice environment. The possible downside is that their observed actions might not be the result of a thorough choice set evaluation. They might have copied their own behavior from someone else, and so on, and so on, the behavior traveled through time. However, depending on the stability of the choice environment and the variation in the original pool of actions, that surviving behavior could be at least as optimal as any SRCM result.

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[56] Given enough time and generations this kind of habit gets encoded in our DNA. While we have talked about habits arising that eliminate doing blind search in your head, this type of efficient “non-search” can go back millions of years, to pre-human generations of past experience from the perspective of our genetic blueprints. For example, after you are born, you do not spend any deliberation time deciding whether to breathe oxygen from air or water (after you are off the umbilical cord of course), your body has an unshakeable belief that you will spend your entire life breathing air. Fish are born with the opposing belief. As a reminder of the necessarily blind, “conjectural” nature of this obviously durable belief and its lack of fit in different choice environments, people do drown, but perhaps only because they are supposed to be able to swim (babies are actually born with a swim reflex).

[57] I recently remodeled my kitchen and had to move the fridge to the living room. At first I would occasionally find myself walking to the old location or even in front of an empty wall before catching my error. Eventually this error rate decreased to zero as a new habit formed for the living room locations. Predictably, when the fridge was retuned to its rightful home in the kitchen, the same transitional errors happened again on the way back to a new (original) habit. There is experimental evidence that reports this phenomena of course, showing that mentally wired choice rules are not as easily switched as a fully fluid and flexible rational choice model would suggest. Cohen and Bacdayan (1994) describe a card color switching problem for example.

[58] In stable choice environments we might actually expect the rational choice process to yield decision heuristics that are optimal in ways that the SRCM is not even considering (Goldstein and Gigerenzer, 2002). Emotions are just one example (Frank, 1988).

Culture as Potentially "Better than Rational" Choice

"There are two kinds of fool. One says this is old and therefore good. The second says this is new and therefore better."—Unknown

In the SRCM, deliberation implicitly takes place in the brain (and lifetime) of a single individual. With the GRCM we can conceive of "deliberation" as something that also happens outside of a single mind as actual or substitute choice trials. We have also seen how we can have a set of action evaluations spread across multiple minds and multiple lifetimes, going back into prehistoric (and even pre-human) times. Our own single man-year time budget for doing choice evaluations clearly pales next to the billions of previous man-years that might have been spent in the same choice environments that we see today. Thus, we should not be surprised when modern attempts to "rationalize" old-fashioned behavior fail when tried in choice environments that have been stable for centuries or longer[59]. We should also not be surprised when similar reforms might succeed in choice environments that are newly dynamic with changed action payoffs. With the GRCM we can explicitly seek to understand the rationality of a habit, norm or custom the same as would the result of any other choice process. We model a choice set and evaluation process (blind variation and selective retention) used to identify the surviving action choices at a particular point in time. Culture and its norms can be an indispensable substitute for actual experience and a guidebook for avoiding bad first guesses. Where culture is lost, worse guesses can be expected to reemerge[60].

Choice Evaluation in Dynamic Environments

We have seen how a variety of static environments might be analytically accessible to rational choice process such as the GRCM[61]. But the main goal of this paper is to suggest how we might use this "choice cost economics" framework to interpret real institutions in the real economy.

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[59] There are many notable examples of modern "innovations" that appeared obviously better and more rational than traditional ways of doing things. Given the extremely stable choice environments in which these cultural norms had survived, they probably should have been appreciated as better-than-rational alternatives. Fertilizer proved inferior to ancient Balinese water temple rice growing rituals (Lansing and Kremer, 1993). "Easy to clean" plastic cutting boards have provided no better sanitation than wooden boards that turned out to have built in antimicrobials (they helped the wood survive when it was a living tree). "Scientific" baby formula proved inferior to the wealth of underappreciated and still unknown ingredients in human breast milk. To economists, the most obvious example is that "rational" central planning of common property (communism) proved inferior to traditionally more decentralized private and customary property regimes that had survived for centuries. Only after such innovations are tried and fail can we know for sure of course, but perhaps we can have a healthier respect for the evolutionary rationality of surviving "choices", *especially* if our own minds can't explain how they work because they are now made somewhat automatically and mindlessly.

[60] Richerson (2011) has noted how wooden canoe technology has been repeatedly invented and lost several times in Pacific island cultures.

[61] We've assumed perfect memory and recall of course, as realistically facilitated by written records, but not always an accurate assumption: the TV show "Concentration" would be a poor fit.

Habits, norms, customs and the like basically arise when a choice problem is "solved" because a particular choice set associated with an unchanging choice environment has been fully evaluated[62]. We can also use the GRCM in more dynamic choice environments such as the real economy, where choice problems are always evolving and where a(x) ➔ a(x,t) instead. There we confront choice spaces that can never be fully explored and that are perpetually changing over time, leaving no choice but to do perpetual evaluations of new and changing choices.

Suppose I take the treasure chest and attach one 2 digit combination lock to the latch, but this lock has an electronic chip in it that changes its combination at some interval of time. It still takes you 6 seconds to do a combination trial and 10 minutes do all 100 combinations, but if the working combination changes in the middle of your initial sequence of trials, you might not find it in the first 100 trials.

If the combination is changing every second, it is essentially random from your perspective. For the same reasons that habit works in a constant environment, a single fixed choice can be the most efficient "choice evaluation" strategy in a randomly unpredictable one. If the combination is changing every day then you will find the working combination as usual, but you will have to search actual combinations again if you need to open the lock next week. If it changes once every 100 years you would not have to search again in your lifetime. If it was every 100,000 years you could think of it as stable (and copy whatever people did 99,000 years ago). You can think of dynamic stability as a ratio of the timescale for complete choice set evaluation relative to the timescale for change in the choice environment payoffs: T_x/T_a. Where $T_x/T_a >> 1$ you can have a random environment and where $T_x/T_a << 1$, you have a stable environment. At both of these extremes a fixed optimal decision rule should emerge, corresponding to the probabilistic and or deterministic certainty in the SRCM. For situations where $T_x/T_a \sim 1$, the need for choice evaluation never ends however and blind search methods and processes can become institutionalized. This is the region of real economic and GRCM behavior to which we now turn.

PART FOUR: Choice Evaluation Institutions

We've looked at some of the implications of costly and time consuming blind choice evaluations in the real world and also methods of minimizing these implications relative to the SRCM. Our exploration in the previous section was not intended to be exhaustive, only to provide enough choice cost concepts so we can start thinking usefully about *search institutions* in the real world[63]. These are the patterns of behavior that would not exist under traditional rational

[62] Focusing on static choice environments also exaggerates the extent to which SRCM can be a reasonable approximation in the real world.
[63] For example we could have discussed creating choice sets, expanding choice sets via creativity and entrepreneurship, and error costs in much more depth.

choice, but exist and persist in a real economy comprised of real people who have no choice but to blindly evaluate new choices all the time.

Once you embrace the reality of blind search, you see it everywhere you look. Our everyday experience with our own substitute choice evaluation is so ubiquitous that we hardly notice it. We squeeze fruit, read labels, smell fish, look inside egg cartons and instinctively put our hands out in front of us in the dark[64].

Huge swaths of human behavior and economic institutions can be viewed anew and explained through the lens of blind search trials and stages that are trials economically allocated in multiple levels or filters of selection. As blind choice evaluation spans from vicarious trials to substitute trials vicarious to actual trials, guesses will generally be more costly and time-consuming but yield ever more reliable information as to actual payoffs. The empirical observation is that choice evaluation processes do visibly progress from many inexpensive searches (brainstorming) to stages with fewer costly substitute experiments to actual choices. Casual observation also suggests that much more rational choice is taking place as external deliberation activity, in real-time, at real cost in the real world, than inside our brains.

How You Got Here

We can concretely illustrate these concepts by now revisiting how you found yourself reading this actual paper, a process with which you are undoubtedly already familiar. The process started with the ISNIE 2011 "Call for Papers", an effective generator of initial variation that attracted hundreds of paper proposals. Once the unread proposals were received, they were ingeniously self-sorted by subject matter characteristics into different batches. These topical batches were then allocated to referees who had specialized mental models for these topics, and who commenced blind evaluations (reading) of their batches in *parallel*. After a month or so the smaller selected set of about 200 approved papers was announced on the ISNIE 2011 website. This is probably where you come into the picture. At some point you clicked on the ISNIE 2011 webpage or opened the conference program. You then decided to look at the accepted papers, implicitly trusting the *substitute choice experience* of the refereeing process that had previously filtered 200 selected papers for you from the larger pool of submitted papers. You then invested *less than a second* per name to skim down the list of authors, looking for those you knew and might have enjoyed reading in the past. (That did not get you here, since I am a new and unknown author to ISNIE). You then, or instead, spent *several seconds* to read paper titles and decided that this title, like some others, was worthy of further investigation. For each intriguing title you then invested an *order of magnitude more time* to

[64] Try muting your senses and going through your day whenever you want an enhanced appreciation (closing your eyes, wearing ear plugs, holding your nose, wearing mittens, etc).

read an abstract. Then, only after all of those *substitute choice evaluation stages,* which saved you from reading whole papers, you found yourself interested enough in this abstract (and others) to download a whole paper and spend at least another order of magnitude of time reading all the way to this word[65].

Along the way you inevitably viewed other names, titles and abstracts of other accepted papers and stopped short of downloading those files. You ruled them out by whatever your own topical or other substitute choice evaluation criteria happened to be. Meanwhile many other people started out on the same name-title-abstract path that leads to this paper but never made it this far.

It should be clear why you could not have followed a traditional rational choice process to this paper, but there were plenty of alternative choice paths to get here. You could have *randomly selected one* paper entry from the ISNIE 2011 list (this one) and downloaded it for complete reading, without further contemplation. Or you could have downloaded *every* accepted paper for reading and done so in order, also without first reading any authors, titles or abstracts. But you almost certainly did not get here by either of these possible paths.

All three possible choice processes above share the same fundamental blindness and each leads to the same action of reading this paper and receiving its (still) unknowable utility. But the first one, which you actually used, differs dramatically from the latter two by being a *rational* choice process. Your mind intervened as the filter that blindly evaluated an enormous choice set of papers, with the help of substitute trials, until your full reading choices were whittled down to a manageable set of full papers. Starting from $u(x)=\{\}$, you made use of efficient substitute search stages and built up enough of a vicarious model to determine that your $u(x_i)$ for this paper exceeded some critical value for you to actually download and start reading it. Hopefully you guessed well.

Since blind search is all we have, there are countless other examples of institutionalized search stages in the real world. Each such activity has a particular choice space that is being explored, starting with cheap and fast trials that progress into more expensive blind search stages before final actual choices. Listed in Table 1 below are a variety of real activities (in no particular order) with their corresponding choice spaces and some representative blind search stages.

[65] If you are reading this because we share a conference panel and professional obligations to read each others papers, then please just play along…

Table 1: Examples of Institutionalized Blind Search Stages

Activity/Goal	**Choice Space**	**Substitute Choice Evaluations**
Reading	Articles	Author, Title, Abstract, Introduction
Writing	Words	Imagination, Typing, Editing, Proofreading
Drug Research	Molecules	Chemical Tests, Animal Tests, Clinical Trials
Product Development	Valuable Features	Prototypes, Focus Groups, Test Marketing
Marketing	Customers	Postcards, Brochures, Trial Samples
Outside Sales	Customers	Contact Lists, Emails, Phone Calls, In-Person Visits
Hiring	Employees	Resumes, Phone Interviews, In-Person Interviews
Job Hunting	Employers	Job Listings, Emails, Interviews, In-Person Interviews
Stock Investing	Public Investments	Financial Ratios, SEC Filings, Phone Calls, Visits
Venture Capital	Private Investments	Business Plan, Due Diligence, Seed Investment
Product Buying	Product Availability	Web Search (Yellow Pages), Phone Calls, Store Visits
Remodeling	Physical Layouts	Imagination, Digital 3D Mockups, Architectural Plans
Dating	People	Online Profiles, Phone Call, Meeting
Performing	Interpretations	Auditions, Practice, Rehearsals, Dress Rehearsals
Writing Software	Binary Strings	Module Testing, Bug Testing, Customer (Beta)Testing
Professional Drafts	Collegiate Athletes	Scouting Reports, Video, Scouting, Private Workouts
College Admissions	High School Students	Applications, Local Interviews, Campus Visits
Carpentry	Wood Length	Freehanding, Measuring, Templating
Eating/Drinking	Food	Seeing, Smelling, Tasting, Swallowing
Car Shopping	Cars	Advertisements, Reviews, Test Drives
Home Buying	Houses	Websites, Phone Calls, Home Showings, Offers
Web Search Engines	Webpages	Headline Results, Page Samples, Clickthroughs
Watching TV	Programs	Listings, Episode Summaries, Channel Surfing

Most of these examples have many more stages than would fit above and these and others can all be easily investigated in detail from a choice cost economics perspective. The surface of empirical choice cost economics is now waiting to be scratched.

PART FIVE: Conclusions and Future Work

A choice cost economics framework has been introduced with a generalized rational choice model (GRCM) for blindly evaluating choices. We have seen how traditional rational choice can be scientifically grounded by reinterpretation as blind search through a choice set. We have also seen how each choice evaluation trials can be given economic attributes such as nonzero cost per trial and nonzero time per trial which may lead to an incomplete search through a choice set. Freed from zero costs and times, choice evaluation trials can be either traditional cognitive simulations, actual choice trials or any substitute choice evaluation with characteristics in between. These trials may also have variable predictive accuracy relative to actual choices. Any combination or sequence of these blind choice evaluation trials can comprise a *rational process* for evaluating the choice set, but we will expect to see least-cost blind searching: efficient use of parallel and modular search algorithms, together with stages of choice evaluation trials ranging from low costs and times to evaluate a choice with low predictive accuracy, to higher costs, times and accuracies, up to full-cost trials of real actions.

This GRCM allows for empirically accurate models of both mental deliberation and evaluation of choices in the real world. The GRCM appears to fit a complete range of static and dynamic “action choice” environments, from rapid mental deliberation, to customs evolved over hundreds or thousands of years, to daily investigations of changing market prices. In contrast, the SRCM might only be empirically valid when it is used to model a time-invariant choice set that has already been completely searched by an actor. The GRCM contains the SRCM as a special case.

The applicability of the SRCM (or GRCM) has been reduced to an empirical question and not one of rational choice methodology or of allegiance to a particular field like neoclassical economics versus behavioral economics (or psychology, sociology or anthropology for that matter). We are freed from the assumptions that make the SRCM occasionally unpalatable. Primarily, we no longer need to assume that people have perfect subjective representations of their actions, $u(x) = a(x)$. Instead, we can explicitly observe how the particular processes they use to evaluate real choices $\{x_i\}$ and actual payoffs, $a(x)$, may create some mental model of choice payoffs, $u(x)$. Then, over time, we might expect to see more accurate vicarious evaluation of potential choices, depending on the characteristics of this process. In other words we can have a clearly modeled path by which subjective expected payoffs $u(x)$ may (or may not) converge to the actual objective choice results, $a(x)$ and $e(x) \rightarrow 0$, as real choices are tried and payoffs recorded in a real environment. We no longer have to assume impossible omniscience to explain good choices, or strange irrationality to explain “bad” ones, we just have to see where we might be in a particular rational choice process.

The GRCM eliminates other major shortcomings of the SRCM. The passage of time arises in each model through the process of non-instantaneous choice evaluations by each actor, whether vicarious or actual choice trials. Genuine ignorance is also revived along with entrepreneurship. Choices may be evaluated accurately through mental simulations, but only within the current bounds on choice sets and only after real payoff data has been acquired from the real world from actual or substitute experience. The GRCM is also deeply consistent with everything we know today about evolution and other sciences, including the biological foundations of our knowledge (Radnitzky and Bartley, 1987).

Future Work

This paper has introduced the idea of using a “choice cost economics” framework to model and understand many aspects of the human behavior patterns that we call the economy. As the use of the word “Toward” in the title suggests, this paper can only serve as an introduction to the theoretical possibilities of anchoring our rational choice models on a proper blind search foundation. It can also only serve as an introduction to the potential empirical implications.

The GRCM will be typically applied by modeling real choice spaces and real bounded choice sets that empirically correspond to particular choice environments. Real choice spaces can be empirically mapped to illustrate the regions and dimensions that have and have not been searched in the real world, by different people. We can investigate real blind search algorithms such as serial or parallel, modular or not, and we can see how search trials are distributed between vicarious, substitute and actual trials in our institutions. We can also study the accumulation and dissipation of different types of search capital.

There are certainly many little puzzles that the SRCM framework fails to embrace or even acknowledge but for which a GRCM analysis may provide a unique perspective. For example: Why do pencils have erasers? Why do stores have return policies? Why choose a patent over trade secrecy? Why do companies make trial-size samples? Why do businesses do test marketing? Why do we see mistakes and failures throughout the economy (including bubbles and crashes)? Why do we observe persistent (but not the same) examples of unemployment, overstocks and other disequilibrium outcomes?

We can also imagine using a GRCM framework to model different organizations as virtual environments that search or select for certain ranges of behavior, just like brains do. In many cases we should expect to find that: *“What emerges is a form of ‘social mind’ that solves complex organization problems without conscious cognition”.*-- Vernon Smith (p428: 2008). We can even think of a real brain as an environment in which potential action choices compete in parallel to be selected as performed action[66].

On the scale of the economy we appear to have a formal modeling framework for incorporating Hayek’s insights about the dispersion of information (1945) and competition as a discovery process (1968). In a parallel search, each individual searcher may have only the tiniest piece of experience, remaining largely ignorant of the entire choice space. But as we have seen, the concatenation of their vicarious models might completely span a huge region of possibilities. A real economy can thus be recognized as a massively parallel dynamic blind search process. Communication works through the price system and minimally overlapping search missions are coordinated by private property, while other more centralized forms of organization may combine both functions.

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[66] You can think of choices like competing strategies in evolutionary game theory but where the environment is the virtual one of the brain. Nash equilibrium is like an SRCM result, while evolutionarily stable strategies are more like GRCM results.

There are also implications for modeling innovation and other economic dynamics. We can do simple agent-based modeling using non-arbitrary GRCM behavioral assumptions with choice cost variables adopted directly from real world data. We can explicitly model evolution and competition in product feature spaces and understand different business strategies in differently evolving landscapes. We can model the difference between an entrepreneur giving the customers what he thinks they want in their mental models and what he thinks they would want after they actually trial his product[67]. We might even find that the ability to do dynamic blind search better than others is a fundamental source of sustainable competitive advantage.

My own current interest is to better understand our searches through real rule spaces and to develop a functionally realistic theoretical understanding of how legislation, common law, customary law and norms are born, survive and die[68]. The demands of this project motivated me toward developing the GRCM framework. For example, substantive mandatory rules (as opposed to default rules), are a category of laws that are basically impossible to find in an SRCM world. However, pseudo-mandatory rules with opt-out based on choice evaluation competence (minimum accuracy of a u(x) vicarious model) appear to be stable in a world with positive choice costs (Lyons 2011).

Just as there are countless examples of blind search in the economy, I believe there are boundless amounts of useful analysis to be done from a blind search and choice cost economics perspective. With luck this paper might catalyze some parallelization of that effort. And if you are reading this sentence, please accept my thanks (and congratulations or apologies as appropriate) for continuing your own search all the way to completion.

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[67] As Henry Ford is reputed to have said: "If I'd asked my customers what they wanted, they'd have said a faster horse"

[68] As we have seen, an imagined rule that might be "efficient" in an economists mind is hardly the same as one that shows actual efficiency in the sense of experienced users happily and repeatedly opting into that particular rule over others. As any entrepreneur can tell you, the real world doesn't care what you *think*, and will let you know when you *do*.

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