The neuroeconomics of habit

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I. Introduction

This chapter is about general principles of neuroeconomics. The principles will be illustrated specifically by mechanisms of habitual choice, and by a simplified computational model of habit which can account for some basic facts about consumer behavior.

We define economics as

the analysis of what causes consequential human choices under scarcity and institutional constraints, and how those choices affect human welfare.

Like most discipline-bounding definitions, this definition is elastic by design. For example, evidence from non-human primates can be useful for economics because humans are primates too. Even though the definition refers to "consequential *human* choices" , what humans and non-human genetic kin have in common could be relevant to understanding what causes humans to behave as they do (through species-general reactions to visual designs, mental states, group dynamics, and status incentives).

Note that our definition of economics specifically does not privilege a particular type of data, or a methodology of measurement or analysis. In particular, we aggressively reject the philosophical stance that economics is restricted to hypothesizing about unobservable mental processes and then testing hypotheses using *only* choice data. For example, in their provocative essay Gul & Pesendorfer (2008) assert that "Revealed preference earns such a central role in economics because this [choice] is the form of evidence that is available to economists". [1]

This assertion is obviously false. Even the early authors of foundational rational choice models allowed that non-choice data could test economic theory (Block & Marschak, 1959; McFadden, 2001). Since the, plenty of economists have used behavioral measures other than choices. A prominent example is subjective well-being (Kahneman & Krueger, 2006; Benjamin, Heffetz, Kimball, & Rees-Jones, 2012). Another is measuring visual attention using mouse-based or eye-tracking methods (Johnson et al Willemsen & Johnson, 2011; Brocas, Carrillo, Wang, & Camerer, 2014; Costa-Gomes, Crawford, & Broseta, 2001;

[1] Some other claims in this paper are baffling. At one point the authors assert that "Neuroeconomics is therapeutic in its ambitions: it tries to improve an individual's objectives".

Reutskaja, Nagel, Camerer, & Rangel, 2011; Fehr & Rangel, 2011; Caplin & Schotter, 2008) Still another is the emergence of genetic data (Beauchamp et al., 2011), which guide deep policy debates about the extent of nature vs. nurture, and can act as "random assignment" in econometric analyses.

In fact, many macroeconomic indicators, such as the Consumer Price Index (CPI), are not actually constructed from choice data, rather they are based on people's recollections about expenses; this is a measure of *memory*, not choice per se. And of course, surveys of beliefs about price inflation (Shiller, 2007) and stock return expectations (Greenwood & Shleifer, 2014) are also used widely in economics.

Neuroeconomists reject the view that theories which include latent variables or algorithms can only be tested by choice predictions. A "choice-only" definition of the field simply mistakes what *data* are used for explaining which type of *behavior* that economists are trying to understand. It should be self-evident that every individual choice— pulling a voting-booth lever, signing a mortgage document, clicking "buy now", planning a child— is implemented by brain activity. Therefore, studying how the brain makes such choices could *conceivably* improve economics *on its own terms*; that is, if economics is truly the science of choice and if more data is preferred to less.

This is not to say that many abstract, difficult to measure, processes — such as regulation and law, market competition, price adjustments, corporate personnel practices, tax rules, investor or consumer sentiment, strength of institutional norms – are not *also* important casual influences on choice behaviour. They are, of course— but such forces are both the product of collective decision-making *and* inputs to an individual's choice, therefore also the product of collective brain activity and inputs to the decision-making process in our brains. Conceivably, they can also be modelled and measured by neuroeconomic data.[2]

Take, for instance, the large and important mission of economics: to help inform sensible welfare-improving policies. Some of the biggest policy challenges— such as obesity, addiction, terrorism, economic desperation, the causes and effects of poverty, investment in education, worldwide climate change, and production and consumption of information – are also deeply influenced by our biology. What proportion of the obesity epidemic, or educational attainment, is due to genetic factors? How much is decision-making impaired by mal-nutrition, or by limited (or even over-abundant!) information? How might suitable behavioural interventions be designed to address these factors in a heterogeneous, diverse, population? To address these issues, the deepest possible

[2] E.g. Douglass North (North, 1991) often emphasized how aspects of long-lived institutions, which are important for organizing economic activity, are embodied by "mental models". An example is the use of fiat money to lubricate trade. To a neuroeconomist, money is a "secondary reinforcer". (It is not a "primary reinforcer", like food, water, warmth, or parental affection, which humans are born liking.) Money acquires subjective value because humans learn it can be exchanged for other valuable reinforcers (via a process of observer-driven Pavlovian associative conditioning, and fine-tuned valuation instructed by parents). While central banks can control the supply of money, introduce different currencies (such as the Euro), and try to stabilize the value of money, at some point those actions influence a process of subjective valuation in the brains of citizens.

understanding about the biology of choice will provide the sturdiest foundation for successful policy-making.

a. Three levels of understanding

The methodology of Neuroeconomics is best illustrated by an important concept introduced by David Marr. Marr was interested in the neuroscience of vision, but was frustrated by how much scientific attention was paid to mechanistic details and how little attention was paid to the functional value of those mechanisms.

In Marr (1982) he described three levels at which behavior can be understood: Computation, algorithm, and implemention. Marr wrote:

> "trying to understand perception by understanding neurons is like trying to understand a bird's flight by studying only feathers. It just cannot be done" (FIND PAGE NUMBER).

The three levels are illustrated in Figure 1.1, for Marr's example of bird flight. Flight is the purpose of the bird's biological system at its highest-level of "computation" (or "functionality", the term we prefer). The middle level is the "algorithm" to achieve flight, which can be described in equations or an engineering flowchart as the flapping of wings. The lowest level is the details of "implementation"—how the precise biological features of the bird's physical system flap the wings to implement the middle-level algorithm.

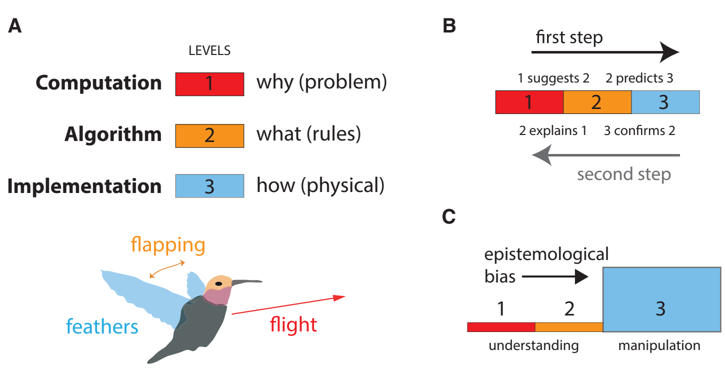

Figure 2. Marr's Three Levels of Analysis
(A) A bird attempts to fly (goal) by flapping its wings (algorithmic realization) whose aerodynamics depend on the features of its feathers (physical implementation). Feathers "have something to do" with flight and flapping, but what level of understanding do we achieve if we dissect the properties of the feathers alone? Bats fly but don't have feathers, and birds can fly without flapping.
(B) The relationship between the three levels is not arbitrary; step 1 comes before step 2: the algorithmic level of understanding is essential to interpret its mechanistic implementation. Step 2: implementation level work feeds back to inform the algorithmic level.
(C) An epistemological bias toward manipulation-based view of understanding induced by technology (black filled arrow).

Figure 1.1: (Krakauer, Ghazanfar, Gomez-Marin, MacIver, & Poeppel, 2017)

Another way to think about these levels is what scientific questions are posed at each level. The functional question is ***Why?*** is the brain organized in a particular way to solve some problem facing the orgamism. The algorithmic question is ***What?*** is being computed. The implementation question is ***How?*** is it computed via biological processes.

The grand hypothesis underlying this three-level framework is that behavior can be best understood by requiring theory and evidence at each level to constrain what's believed about the other levels. Consider flightless Galapagos cormorant birds. They do not need to fly because they don't need to escape. They are not threatened by ground predators in their habitat, they nest on rocks slightly above the high tide mark (as opposed to nesting on a cliff or in a tree) they do not nest in trees, and they don't migrate long distances. (Who needs flapping wings? No thanks.) The implication of these altered functionality— driven by its ecological niche-- is that the algorithmic control of wing-flapping, and its consequence mechanistic details, should be entirely different in these Galapagos cormorants, compared to the other 39 cormorant species that do fly (Burga et al., 2017).

This three-level approach can easily be applied to the social sciences. However, in our view, microeconomic theories of individual choice are largely concerned with describing behaviour at the functional level (if only partially). Consider the example of choosing bundles of objects which have higher subjective utility, subject to a budget constraint of income.[3] In general, these theories impose axioms on behaviour under which a rational agent will reveal their utility maximizing alternative. Or said another way, the laudable goal of consistent (rational) behaviour is why agents might maximize some utility function.

However such theories only partially address the functional question; generally they do not specify the adaptive function of maximization or preferences. It could be supposed that if two organisms both have the same stable subjective values for goods (utilities), the one that allocates scarce mental resources to the maximization will have an advantage. But what adaptive purpose does that outcome serve? And of course standard theory is purposefully silent on both the algorithms that people might use to implement (or approximate) this maximization, and its actual physical implementation subject to biophysical constraints.

A few literatures in economic theory have taken on the challenge of integregating these three levels, using different methods (Woodford, 2014; Fehr & Rangel, 2011; Rayo & Becker, 2007). One path derives the types of utility functions that would emerge under selection pressure in a particular choice environment (Robson, 2002). For example, it is commonly held that risks are valued by weighting the utility of separate outcomes by their subjective probabilities. Higher aversion to risk is mathematically equivalent to having a more concave utility function. But, again, what adaptive purpose does concave utility serve? In fact, why even have a utility function at all?

Robson (2001) considered a simple example in which economic outcomes, or fitness, is determined by a simple two-armed bandit problem. In such a simple setting, it is optimal to choose the bandit with the higher probability of yielding a reward, therefore evolutionary forces might simply select for agents who always choose this bandit. But such a trait would clearly be sub-optimal in a world in which the probabilties of the bandits can change. In this world, Robson shows that an agent endowed with a utility function over outcomes maximizes fitness. Moreover, the shape of the utility function is determined by the energy requirements required for procreation (or in the language of economics, the

[3] These theories are popularly extended to include aversion to risk, rewards spread out over time, and social preferences for what other people consume.

baby production function must be concave). This is a functional argument for the existence of utility maximization.

How might such a solution be implemented at the algorithmic level? When agents do not know the sample probabilities *a priori* – therefore must learn them – simple reinforcement learning algorithms offer computationally efficient solutions to the bandit problem (Sutton & Barto, 1998) . In RL models, the agent samples a bandit and updates a value function V_t(x) according to whether the sample was succesful or not. This update is implemented in the form of a *reward prediction error*: the amount that the reward deviated from the predicted value of the bandit, $R(x) - V_{t-1}$_(x).

$$V_t(x) = V_{t-1}(x) + \lambda (R(x) - V_{t-1}(x)).$$

In the following trial, the agent then chooses the bandit with the highest value and updates it. As the agent samples more from each bandit, $V_t(x)$) will converge to the true expected reward. How well this algorthm performs depends on the properties of the bandit (like the variance of its reward distribution), but generally these algorithms perform well when each choice is subject to some exploration error. This ensures that the agent does not initially reject actions simply because of a few poor outcomes. Remarkably, this algorthm also works well when the probability dsitribution is non-stationary; the exploration error ensures that all bandits will be continuously sampled, implementing a tradeoff between exploration and exploitation. The simplicity of this algorithm, and its ability to guide behaviour in such tasks, has spawned the growing field of machine learning (Sutton & Barto, 1998).

Perhaps the most striking property of reinforcement learning was the discovery that dopamine neurons in the mammalian brain encode a reward prediction error. In a series of foundational experiments, the activity of dopamine neurons have been shown to correlate with a general form of the reward prediction error which allows for the linking of sequential cues within a trial (Schultz, Dayan, & Montague, 1997; Glimcher, 2011) . These experiments thus described the neural computations for implementing a reinforcement learning algorithm, and form some of the foundational results in the fields of neuroeconomics.

The linking of all three levels, functional, algorithmic, and biophysical implmentation, clarifies the current goal of neuroeconomics:

> **Neuroeconomics seeks to establish what algorithms of economic choice achieve high-level** functional **goals, and are actually implemented by neural circuitry and other biological forces (such as genes and hormones).**

That is, the goal is to bind together ideas and evidence at all three levels of analysis (Niv & Langdon, 2016).[4]

Next we will develop these ideas with specific reference to the concept of habit.

II. Habit

A healthy person going about their day is constantly shifting between highly automatic habitual choice and interruptions for thoughtful deliberation. For example, as Sharon gets in the car for the Monday morning commute, she plunks her home-brewed coffee in the drink-holder, punches FM station setting 2, and backs out of the driveway. She has done this many times before; so she does so now with minimal attention and may not even remember having done many of the steps. She is using habitual control.

On her way to work, suppose the radio station says that there is terrible traffic on highway134 in Burbank. Construction began last week and is expected to continue for two more weeks. If Sharon is deep in habit mode, she does not even notice the radio announcement. She'll get stuck in traffic and then encode a negative "prediction error" (a gap between the driving outcome she experienced today and what she experienced in the past). After a few days of getting stuck in traffic-- perhaps only one day, if she learns quickly-- she will be alert to the announcement and will quickly decide what to do.

But suppose Sharon has only made this commute for a few days. She is not yet in habit mode, and instead does what neuroeconomics calls a "model-based" (or "goal-directed") decision. In this choice mode, the first traffic message is processed by a system that quickly sprouts mental decision trees with implicit conditional probabilities and alternative choices. The trees have a "terrible traffic" branch which lead to bad outcomes from staying on Highway 134 (such as "frustration", and "late for work"). Sharon's mind rapidly starts thinking through alternative decision branches. She judges the combination of likelihood and quality of outcomes from actions along those newly-imagined branches and chooses a new route. She'll get off the packed highway 134, go along a Cahuenga detour, and stop at a favorite coffee shop. She can call into her 9 am meeting from there.

The concept of habit has, of course, been discussed for a long time in individual and organizational psychology ("routines" [5]), in sociology anthropology ("rituals"), and in economics. The Nobel laureate economist Gary Becker (Becker, 1996, p.9) wrote "I believe the main reason habitual behavior permeates most aspects of life is that habits have an advantage in the biological evolution of human traits."

Our neuroeconomic model of habit posits that behavior is the output of one of two neurally-distinct systems for choice, called habitual and goal-directed.[6] In habit mode,

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[4] In practice, the hardest and least understood link is to the functional levels. Because human decision is often complex, and highly social and acculturated, it is much harder to link algorithms to function than it is for simpler species.

[5] See sociological discussions about norms and organizational "routines" (Nelson & Winter, 1982; Biggart & Beamish, 2003; Hodgson & Knudsen, 2004). Routines are company-level habits.

[6] "Dual system" neuroeconomic models have been proposed before. The closest in spirit to ours is Benhabib & Bisin (2005)'s model of automatic and controlled interaction in savings decisions (and

people who face a familiar choice situation make the same choice they did the last time if that choice was reliably rewarding. The habit mode is fast, implicit (i.e., often not conscious), and can make optimal choices in a sufficiently stationary world. In preference-based mode, people use a subjective "model"[7] to evaluate likely values of different goods or activities. The goal-directed mode is slow, avoids habit mistakes when the choice environment changes, and is more likely to be conscious (in psychological language, "explicit"; i.e., people can describe what they are thinking in a way that an observer following their instructions could approximately reproduce their behavior).

a. Neuroscientific background

The distinction between habit and preference-based systems, as we model it, first gained precision in animal learning, then quickly became evident in a variety of neuroscientific studies.[8] This section will first sketch precursors to habit in biology, then hone in on how we define habit.

Automatic behaviors are ubiquitous in nature. All mammals have reflexes that are highly automated and do not take conscious thought. Lorenz (1935) showed that newborn ducklings will immediately bond with and follow around their mother as soon as they can walk— and if the mother isn't present they will follow around a human. Animals exhibit fixed action patterns when confronted with an "innate releasing mechanism" in response to an evolutionarily-important stimulus (e.g., mating dances by birds; (Tinbergen, 1951)). Later scientific study, in simple domains such as rodents running through mazes for food, showed how chained sequences of actions become rapid and automatic. Neural activity is observably reorganized as sequences are learned (Graybiel, 1998; Smith & Graybiel, 2016; Smith & Graybiel, 2014) .

The first step in our approach is forming a precise definition of habit, with empirical content. Adams & Dickinson (1981) defined a habit as a behavior that is so "overlearned" that it is repeated even when rewards are devalued. For example, Adams & Dickinson (1981) conducted a seminal a study in which rats were trained to press a lever for sucrose pellets in ten training sessions, over 500 rewarding trials. Lever-pressing becomes rapid and automatic. After this training the rats are allowed to eat as much sucrose as they want, but it is paired with lithium chloride. This pairing makes the rats mildly ill and creates a taste-aversion so that they dislike sucrose. The sucrose has been "devalued".

After devaluation, the rats are then allowed to lever-press again (with no reward presented). Rats press about 4.4 times per minute after sucrose was devalued, about the same as 3.7 times per minute for control rats (for which there was no devaluation). Five hundred trials of training apparently built up a habit to press the lever, *even when pressing*

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mention predictions about neural activity and response time). However, there is no dynamic concept akin to habit in their approach.

[7] In cognitive neuroscience the two systems are often called "model-free" and "model-based". We use the term "preference-based" here because it makes the contrast between our approach and utility-maximization (which is what we call preference-based) more clear.

[8] Psychological ideas and measures of habits proceeded in a parallel track but have not been closely linked to biological mechanisms (Wood & Rünger, 2016).

does not achieve a desirable goal. In a group with less training (100 trials) rats in the devalued condition *did* press less often, only 1.7 times per minute, than control rats. Numerous replications of this classic result can be found in neuroscience and psychology (Dickinson, 1985; Dezfouli & Balleine, 2012).

In microeconomic terms, the rats are persistently "demanding" food at the same rate, even after its quality has changed dramatically. This is naturally described as a zero quality-elasticity (an elasticity is the percentage change in demand relative to the percentage change in another variable, such as price or income). While in the animal experiments the price has not been changed, it is a small leap to expect that a habit defined as zero quality-inelasticity will also exhibit zero price-elasticity.

In the neuroeconomic view, a habit is therefore *defined* as a choice pattern with zero short-run elasticities. This neuroeconomic definition links the psychological concept of habit with a behavioral measure from economics. It also identifies precisely what to look for in economic data—viz., persistent choices and a zero or low reaction to price changes. Many studies since then have established the basic distinction between habit and goal-directed control, and explored their neural mechanisms (Dickinson, 1985; Dickinson & Balleine, 1993; Yin & Knowlton, 2006). Some studies even seem to pinpoint what brain areas are used to execute habits. If a habit is short-circuited, then animals should cease to respond when reinforcers are devalued (i.e., they *will not* respond for worthless rewards, as in the experiments just described.) Indeed, causally extinguishing activity in the dorsolateral striatum with neurotoxins erases habit in rats (Yin, Knowlton, & Balleine, 2004; Kyle Stephen Smith & Graybiel, 2014, Fig.1). The homologous area of dorsolateral striatum in humans is also activated by fMRI when people execute habits (Tricomi, Balleine, & O'Doherty, 2009) Unusual activity in this area, in concert with reduced dorsolateral pre-frontal activity, is linked to addictive behaviour in humans (Wesley et al., 2014).[9]

As Gary Becker's quote anticipated, a *mixture* of habit and goal-directed control is an ideal way for healthy, busy, humans to behave. In developed economies, people make many choices every day, and only have a very scarce amount of cognitive control (or "executive function"). Habits put the brain on "auto-pilot" and conserve mental resources (see Duhigg (2012) for a good popular account). Habitual choices are also approximately optimal if the subjective values of available goods are not changing too much. However, habits miss opportunities to switch to choices that have become more highly-valued. Therefore the key feature of a well-functioning habit/goal-directed mixture is a mechanism for *arbitrating* between the two systems.

Research in theoretical neuroscience proposes that arbitration occurs because the brain keeps track of the reliability of rewards from both habitual and goal-directed choice in some way. In the two-process system more reward-reliable takes control (Daw, Niv, & Dayan, 2005; Keramati, Dezfouli, & Piray, 2011). Ideally, this arbitration should break habits when they become mistakes, and should hand control back to the habit system when choice values stabilize (i.e., reward reliability is high). Lee, Shimojo, & O'Doherty (2014)

[9] (Wesley et al., 2014) elaborate that "the evolutionarily young executive system [pre-frontal] … works in concert with the older limbic system [striatum] for optimal decision-making. When these systems are functioning sub-optimally decision-making becomes impaired." Note that we are focusing on a model of healthy individuals, making relatively mundane, regular choices which are not likely to be biologically addictive. However, this same system could malfunction in addictive choice environments.

provide the first fMRI evidence of this process. They identified activity in lateral prefrontal cortex and frontal pole encoding reliability signals-- defined as the chance of zero error in predicting reward-- for both habitual and goal-directed choices.

b. A simple neuroeconomic model of habit

Here we present a simple model that formalizes our distinct notions of habit-based and goal-directed decision-making. A key feature is how control over behavior is transferred from one decision-making mode to the other. To link the model with familiar economic concepts of utility-maximization, we refer to the goal-directed mode as "preference-based". The model is abbreviated HP, for habit-preference. We will show that the HP model produces new insights into how consumers respond to incentives and disincentives as captured by a basic economic measure – price elasticity of demand.

Formally, a consumer must choose one of two product options, A and B, at each time-period $t = 1,2,3 \ldots$. Let c_t denote the consumer's choice at t and $u_t(x)$ denote the subjective utility from consuming option x at t. In *preference-based* choice, the consumer considers all available options and chooses the best among them:

$$c_t = \begin{cases} A, & u_t(A) > u_t(B), \\ B, & u_t(A) < u_t(B). \end{cases}$$

In *habit-based* choice, however, the consumer simply repeats her previous choice:

$$c_t = \begin{cases} A, & c_{t-1} = A, \\ B, & c_{t-1} = B. \end{cases}$$

The next step is to specify a rule that determines whether a consumer operates in preference-based mode or in habit mode at any given time. Following suggestions and evidence in neuroscience we propose that the consumer implicitly forms predictions regarding the value of each option and encode prediction errors when goods are consumed. The predicted value of option x at time t, denoted $r_t(x)$, is a time-weighted average of past utilities from consuming x:

$$r_t(x) = \begin{cases} (1-\lambda_r) r_{t-1}(x) + \lambda_r u_{t-1}(x), & c_{t-1} = x, \\ r_{t-1}(x), & c_{t-1} \neq x. \end{cases}$$

The parameter λ_r is a constant learning rate (between 0 and 1) that reflects the degree to which predictions about the value of x adjust to its present experienced utility $u_{t-1}(x)$. When $\lambda_r = 1$ predictions respond immediately to subjective value. When λ_r is low, predictions respond slowly to changes in subjective value. If x was not chosen at $t-1$, there was no new information about its utility, so the implicit prediction of x's value will not change from $t-1$ to t.

Notice that the updating equation for when x is chosen can also be written as $r_{t-1}(x) + \lambda_r [u_{t-1}(x) - r_{t-1}(x)]$. In other words, the new reinforcement prediction is the old value plus the learning rate λ_r times the "reward prediction error" (RPE) $u_{t-1}(x) - r_{t-1}(x)$.

Besides forming predictions regarding the value of each option, we also assume that the consumer tracks the *reliability* of these predictions. We let $d_t(x)$ denote the "doubt stock" for option x at time t. A low value of $d_t(x)$ means the consumer implicitly "trusts" (i.e. has little doubt in) the current prediction $r_t(x)$. Doubt is low if past predictions $r_{t-k}(x)$ ($k = 1,2,\ldots.$) have been good predictors of actual past utilities $u_{t-k}(x)$. Doubt is high if predictions have been far off.

Doubt is updated based on the *absolute* (RPE), $|u_t(x) - r_t(x)|$. (In principle, the impact of the absolute RPE on doubt could be stronger or weaker depending on whether the RPE is positive or negative, but here we assume that positive and negative RPEs are weighted.)

Formally, the doubt stock evolves according to the following rule:

$$d_t(x) = \begin{cases} (1-\lambda_d)d_{t-1}(x) + |u_t(x) - r_t(x)| & c_{t-1} = x \\ (1-\lambda_d)d_{t-1}(x) + 1 & c_{t-1} \neq x \end{cases}$$

where λ_d is a constant learning rate between 0 and 1. This learning rate is similar to λ_r except that λ_d represents the degree to which doubt changes in response to RPEs. For simplicity, we will assume $\lambda_r = \lambda_d = \lambda$ going forward, though empirically they could be different. We also set $d_0(x) = \lambda^{-1}$ for $x = A$, B, which ensures that the initial doubt for a given option will stay the same as long as that option is never chosen.

Our rule for updating the doubt stock indicates that if x was chosen at $t-1$, the doubt stock at t will then increase by the absolute RPE. If $u_t(x)$ is not changing while x is repeatedly chosen, then the RPE $r_t(x) - u_t(x)$ will approach zero in absolute value. The RPEs will get smaller and smaller and the doubt stock will shrink toward zero. But if $u(x)$ suddenly changes, a large RPE will change the predicted value of x and will also cause a jump in the doubt stock.

If x was not chosen at $t-1$, the doubt stock at t increases by a constant amount, which we fix to 1. This implies gradual growth in the doubt stock for an option that is consistently unchosen. This model choice reflects the notion that one cannot be too confident in implicit predictions about the value of an option that has not been chosen in a long time, because these predictions have not been "tested" against the true utilities they are supposed to predict.

To close the model, habit-based decision-making is used if and only if the doubt stock associated with the previously-chosen good is below some threshold, $\sigma < 1$. This leads to the following choice rule:

$$c_t = \begin{cases} c_{t-1}, & d_{t-1}(c_{t-1}) < \sigma, \\ \arg\max_{x \in \{A,B\}} u_t(x), & d_{t-1}(c_{t-1}) \geq \sigma. \end{cases}$$

For a new consumer with high initial doubt stocks for both goods, preference-based decision-making will guide her choices. That is, she will evaluate both options' utilities and choose the best among them. Suppose the first choice is A. If utilities are relatively stable, the RPEs will shrink and reduce the doubt stock over time. In the simplest case, when utilities do not change at all, after t periods the doubt stock will have shrunk by a factor of $(1-\lambda)^t < 1$. Once $d_t(A)$ falls below σ, habit mode takes over and the consumer continues to choose good A *without even considering good* B. Note that this means habit-model choice can be measured by persistent in choosing A, but also by rapid choice and inattention to alternative products.

The model highlights the economizing value of habit. The cheapest process that implements the choice procedure first perceives an environmental state, recalls the previous choice c_{t-1} that was made in that state, and checks if the doubt stock $d_{t-1}(c_{t-1})$ is less than σ. If the answer is Yes the habitual choice is executed. In this choice procedure, a habitized person *does not even need to recall the utility of what they are buying*. They only need to recall the previous choice and its associated doubt stock. In terms of neural activity, we would expect to find signals associated with value uncertainty (=doubt stock) in habit mode, and a weaker or even nonexistent signals associated with reward prediction and with subjective value. Indeed, the ability to execute a choice rule without recalling those signals is exactly what makes habit mode appealing.

It can be shown that initial preference-based choice will persist in this case as long as $t < \ln(\sigma\lambda)/\ln(1-\lambda)$, after which habit takes over.[10] This switching point is *decreasing* in the threshold σ and in the learning rate λ. Habit mode will maintain control until it is interrupted by a series of sufficiently large RPEs, caused by changes in A's utility, pushing $d_t(A)$ above σ.

Recalling that the doubt stock is driven by *absolute* RPEs, we can see that both "good" ($u_t(A) > r_t(A)$) and "bad" ($u_t(A) < r_t(A)$) surprises can jolt the consumer out of habit mode, prompting the model-based consideration of other options. Thus, even if good A's price or quality improves, this improvement will trigger a jump in the doubt stock, which could lead the consumer to abandon the habit and choose B.[11] This is a surprising prediction of the HP model with a single response to doubt stock (and may well be wrong).

The way in which our model generalizes utility-maximization is now apparent. Suppose a consumer is in habit mode for A when the relative utilities of A and B change so that $u_t(A) < u_t(B)$ (e.g., B gets cheaper). If the changes are small and $\sigma > 0$, she will continue to choose A even though B is now better. In utility-maximization, however, $\sigma = 0$ so the consumer is never in habit mode. Thus, the simple model in this two-good case generalizes standard consumer theory.

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[10] To see this, note that in this example $d_t(A) = \lambda^{-1}(1-\lambda)^t$, while preference-based choice is maintained as long as $d_t(A) < \sigma$. Combining these expressions and solving for t then yields the switching time expression given above.

[11] Here is a motivating example of how a positive prediction error might shift habits. Suppose a family goes to the same Chinese restaurant every Sunday and orders their same, favorite dishes. One Sunday two of the dishes are unusually good. Intuitively, even though the dishes taste better, positive prediction error increases doubt stock (perhaps triggers in an inference that there is a new chef) and could lead to deliberate evaluation of other dishes they did not as much like in the past.

Next we show two interesting implications of the simple habit model for price elasticities.

c. **Habit and price elasticities**

The sensitivity of demand to a change in price—elasticity-- is the percentage quantity divided by percentage price change. This elasticity is a unitless number (because percentages are unitless), so that elasticities can be compared across types of goods. Elasticities are workhorse numbers that are used to define monopolization or addiction (low elasticity) and competition (high product-specific elasticity), to define substitutes and complementary goods (=cross-price elasticities that are positive and negative respectively), and to estimate numerical effects of policy changes such as increasing the tax on gasoline.

An ongoing challenge for neuroeconomics is whether understanding basic neural computational processes, and constructing models about those processes (at Marr's algorithmic level), can say something novel about basic questions in economics. We developed the HP model specifically to say something about a very basic economic construct— price elasticity.

There is a simple link between neuroscience and elasticity, through our concept of habit. Following Adams & Dickinson (1981), neuroscientists think the clearest marker of habit is insensitivity to devaluation of outcomes. This behavioural tendency is exactly the same as revealed preferences that indicate zero price (or quality) elasticity. The two disciplines hit upon the same idea from wildly different angles.

Using the two-goods HP model, we can explore the model's implications for price elasticities in a stylized consumer market when prices change. We focus in particular on the anomalous demand patterns that may arise after consumers have formed entrenched habits.

We assume the market is comprised of a unit mass of consumers with symmetrically heterogeneous preferences in that, when the prices of the goods are equal, $p(A) = p(B) = \bar{p}$, the utility difference $u(A) - u(B)$ is uniformly distributed between -1 and $+1$ across all consumers. Next, we consider the effect of a sudden change in the prices of goods A and B by Δ^A and Δ^B, respectively (so that $\Delta^x > 0$ means good x has become more expensive while $\Delta^x < 0$ means x has become less expensive). Letting $\mathrm{Q}^A(\Delta^A, \Delta^B)$ represent the quantity demanded for good A in the period when these price changes first occur, good A's *own-price elasticity* quantifies the effect of the price change Δ^A on the demand for A and is given by:

$$\eta^A(\Delta^A|\Delta^B) = \frac{[\mathrm{Q}^A(\Delta^A,\Delta^B) - \mathrm{Q}^A(0,\Delta^B)]/\mathrm{Q}^A(0,\Delta^B)}{\Delta^A/\bar{p}}.$$

The *cross-price elasticity* quantifies the effect of B's price change, Δ^B, on the demand for A:

$$\eta_C^A(\Delta^B|\Delta^A) = \frac{[\mathrm{Q}^A(\Delta^A,\Delta^B) - \mathrm{Q}^A(\Delta^A,0)]/\mathrm{Q}^A(\Delta^A,0)}{\Delta^B/\bar{p}}.$$

There are four qualitatively distinct ways in which demand in a market with habituated consumers can depend on price changes, each of which represents a different-colored region of the following graph:

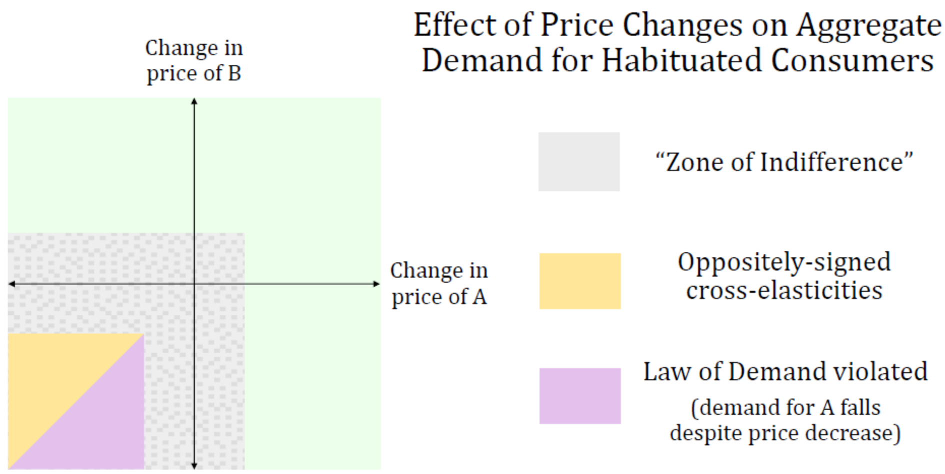

Figure 1: Changes in demand for A as a function of price changes of A and B in a market of consumers with pre-established habits (half for A, half for B).

The green area in Figure 1 represents a “normal” region in which price changes induce the same “standard” effects on demand for each good as for consumers in the preference-based decision-making mode. In particular, consumers’ aggregate behavior satisfies the “Law of Demand.” That is, demand for A falls as its price increases ($\Delta^A > 0$) and rises as its price decreases ($\Delta^A < 0$), as captured by a negative own-price elasticity, $\eta^A(\Delta^A|\Delta^B) < 0$. Furthermore, demand for A rises with an increase in the price of its substitute B ($\Delta^B > 0$) and falls with a decrease in the price of B ($\Delta^B < 0$), as captured by a positive cross-price elasticity, $\eta_C^A(\Delta^B|\Delta^A) > 0$ (the converse also holds: $\eta_C^B(\Delta^A|\Delta^B) > 0$).

Of particular interest, the remaining regions highlight three ways in which habituated consumers will exhibit nonstandard responses to price changes, as predicted by our model.

Zone of Price Indifference (*Gray*): Within the gray region, the price changes Δ^A and Δ^B have no effect on demand; that is, price-elasticities are zero: $\eta^A(\Delta^A|\Delta^B) = \eta_C^A(\Delta^B|\Delta^A) = 0$. This so-called *zone of price indifference* (ZPI) exists because price changes within the zone are either too small (in magnitude) to jolt consumers out of habit mode, or because a price change is sufficiently favorable to preclude switching to the other good even when both options are considered. For example, a huge price decrease for good A can prompt consumers habituated to A to consider both options, but since A is even more appealing in relation to B at their new prices in this region, those who have been consistently choosing A will continue to do so – except now based on a preference for A rather than a habit.

In line with this prediction, many marketing studies have documented near-zero price elasticities in a measured ZPI surrounding a reference price.[12] Estimates of the size of the ZIP are about 10% of the current price (Han, Gupta, & Lehmann, 2001). They cluster all consumers into two segments based on several observables. The two segments appear to

[12] The ZPI is also called “latitude of price acceptance” in marketing.

correspond to more price-sensitive and more habitual shoppers.[13] There is mixed evidence that indifference thresholds increase when prices are more volatile, consistent with "hysteresis" stemming from the option value of waiting for a better deal when prices are variable (Richards, Gómez, & Printezis, 2015). This is not part of our model.

Law of Demand Violated (*purple*): According to our model, the Law of Demand can be violated under the right conditions among consumers with pre-established habits. Namely, within the purple region of Figure 1, $\eta^A(\Delta^A|\Delta^B) > 0$, as a decrease in the price of A paradoxically leads to a decrease in demand. Intuitively, in this region price cuts for A are sufficiently large to induce a shift to preference-based decision-making, but insufficiently large to compensate for the even larger price cut for B, leading some consumers to switch from buying A to buying B. If A had maintained its original price, however, these consumers would not have noticed B's price cut and would have therefore continued choosing A (even though B now represents a better deal). Notice that this surprising violation is *not* due to the usual Giffen good conditions.

Oppositely-Signed Cross-Price Elasticities (*orange*): Standard economic treatments suggest that the relationship between B's price and demand for A should be qualitatively the same as the relationship between A's price and demand for B. Namely, when A and B are substitutes (as in our model), a price change for one good should shift demand for the other good in the same direction. If chicken and beef are substitutes, then when the price of beef goes up, demand for beef goes down (the own-price elasticity is negative) and demand for chicken goes up (the cross-price elasticity of the substitute good is *positive*). Other goods are complements, like computer hardware and software. For such goods, the cross-price elasticities should be *negative*.

In our example, A and B are substitutes so the cross-price elasticities $\eta_C^A(\Delta^B|\Delta^A)$ and $\eta_C^B(\Delta^A|\Delta^B)$ should both be positive. Within the orange region of Figure 1, however, the cross-price elasticities have opposite signs, $\eta_C^A(\Delta^B|\Delta^A) < 0 < \eta_C^B(\Delta^A|\Delta^B)$, as the price decreases $\Delta^A < 0$ and $\Delta^B < 0$ both shift demand towards A and away from B. The reason B's price cut shifts demand towards A in this case follows from the fact that the Law of Demand for B is violated within this region (not to be confused with the purple region, where the law is violated for A), leading to the peculiar effect on demand for A. As noted in a review by Bonfrer, Berndt, & Silk (2006), empirical studies frequently find that estimated cross-price elasticities in pairs of goods have opposite signs. There is no consensus about how asymmetries should be interpreted, or whether they reflect measurement error. The HP theory gives one possible explanation.[14]

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[13] Their algorithm compares fits for two to five clusters and picks out two as the best-fitting (meaning additional clusters did not change overall fit much). Other studies have found two or three segments (Bucklin & Gupta, 1992). This is consistent with a two choice-mode simplification.

[14] In a meta-analysis of 15 studies on grocery purchases, Sethuraman, Srinivasan, & Kim (1999) report that about 10% of 1,060 cross-price elasticity estimates are incorrectly signed. The authors suggest these incorrectly-signed elasticities were probably due to measurement error. We believe this explanation is

Asymmetric Responses to Gains and Losses

The model can also generate a gain-loss asymmetry: Demand is more elastically responsive to increases in the price of good A than it is to equal-sized price decreases. This prediction is most apparent when A's price change is sufficiently large to escape the ZPI for a price increase $\Delta^A > 0$ but $|\Delta^B|$ is small enough to keep consumers in the ZPI for a price decrease $-\Delta^A < 0$ of equal magnitude. The intuition is that both an increase or a decrease in A's price create RPEs that are equal in absolute value. Both changes will push the doubt stock $d_t(A)$ above the threshold σ, triggering preference-based choice– but only among consumers who were habituated to A. While the price increase will shift demand away from A (among consumers previously-habituated to A), the price cut would not draw a similar share from consumers habituated to B, if $|\Delta^B|$ was too small to induce these consumers to consider A at its new price.

This type of increase-decrease asymmetry was first shown by Putler (1992) in an empirical analysis of the demand for eggs. He estimated elasticities for price increases and decreases to be -.78 and -.31, respectively. Since then, many studies have confirmed this asymmetry (Mayhew & Winer, 1992; Hardie, Johnson, & Fader, 1993; Kalyanaram & Winer, 1995; Han et al., 2001). The standard behavioral explanation is that loss-aversion from paying a price higher than a reference price causes the asymmetry. The loss-aversion explanation is certainly plausible (and is consistent with much other evidence of loss-aversion in consumer behavior e.g. Ahrens, Pirschel, & Snower (2017)). However, we can get the same theoretical result from the concept of habit, without loss-aversion. Intuitively, habit and the doubt stock threshold create a pseudo-loss aversion, because the habituated A buyers are more sensitive to the price increase (a loss, for them) than the habituated B buyers are to the small change in the price of B. Furthermore, the HP model makes a new prediction: the increase-decrease asymmetry will only be seen for large enough price changes in one good A when other substitute good price changes are small. If both changes are large enough, there will be no gain-loss asymmetry as Putler and others found.

d. Comparison with economic approaches

Within the utility-maximization revealed preferences approach, there is only one convenient ways to describe habits: A habit must reflect an increase in the utility of a particular based on how often it was chosen in the past.[15]

In economics, habit has therefore been modeled as "state-dependence" (Farrell & Klemperer, 2007; Dubé, Hitsch, & Rossi, 2010), in which preferences for a good are affected

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probably correct in many cases, but it is also possible that anomalous findings such as these are too quickly dismissed because there is no theory about why signs would be wrong. We offer such a theory.

[15] A habit could also result from valuable learning-by-doing, which makes it costly to switch to a new choice. (For example, driving an automatic transmission long enough makes it difficult to switch to a manual stick shift.) In these cases the increase in utility of the habitual action is naturally interpreted as a reduction in effort cost.

by the previous purchase history, summarized as a "state" variable.[16] (The terms "brand loyalty" and "inertia" are also used, typically synonymously with state-dependence.) Persistence in consumption is also thought to be due to complementarity between past and current consumption (Pollak, 1970; Ryder & Heal, 1973; Becker & Murphy, 1988; Crawford, 2010): That is, the marginal utility of consumption in period t is higher if the same good has been purchased in previous periods t-1, t-2, etc. $\partial u_t(c_t, c_{t-1})/\partial c_{t-1} > 0$. This adjacent-complementarity approach is plausible, but it does not say anything interesting about habit at any of the functional, algorithmic, or mechanistic levels. It is a reduced form of a hidden neural computation.

If you were to build a machine to exhibit habits as described by these economic models, you would simply increase utilities of goods based on how often they were chosen in the past. Such a machine would not have any cost savings from exhibiting habit in this way (unless the cost savings are included in a net utility calculation).

The role of the threshold σ in our approach is similar to threshold approaches used in other areas of economics, where there is behavioral stickiness or rigidity unless there is a sufficiently large change in market conditions (Slade, 1999; Caballero & Engel, 1999; Cecchetti, 1986). Rigidity in this context is usually ascribed to frictions or "menu costs".

Our approach is also related to macroeconomic work on "inattentive consumers". For example, Reis (2006) derives how frequently consumers re-evaluate their consumption plans when planning is costly. Consumption during periods of inattention is similar to habit, but decisions to plan are carefully computed by optimization. In contrast, we have opted to make the habit system as 'dumb' and automatic as possible.

Of course, there is plenty of solid empirical evidence of choices which *seem* to be habitual, in the sense that people persist in a regular choice even when it does not accomplish their desired goal, or when it leads to a regretted mistake. For example, studies of people driving in simulators for many hours (Charlton & Starkey, 2011) demonstrate that highly-practiced drivers become inattentive. And in actual driving, near-crashes and crashes are often associated with inattention (NHTSA, 2006).

Consumer purchase data usually show strong patterns of brand loyalty, typically implemented as dependence of current choice on choice history. (This dependence will be exhibited by consumers choosing according to the HP model, but the dependence is not built in as a primitive.)

A particularly interesting study is (Bronnenberg, Dubé, & Gentzkow, 2012). They studied the products that US customer purchased after moving from one state to another. They find substantial persistence in what brands consumers buy: In the first four years after moving, consumers respond to just 60% of the new supply conditions they face (implying a 40% habit 'strength'). The implied habit strength is weaker for people who

[16] In macro-finance, "habit formation" preferences take the difference between a household's aggregate current consumption level and a weighted average of previous consumption (Abel, 1990; Constantinides, 1990; Boldrin, Christiano, & Fisher, 2001; Campbell & Cochrane, 1999). This is a different definition than used in consumer theory or in our model. It more closely resembles the idea of a "hedonic treadmill" which reduces subjective value because of reference-dependence.

moved when they were younger.[17] (Consistent with this finding, brand loyalty is generally shown to be stronger among older consumers; Lambert-Pandraud & Laurent (2010)).

An interesting empirical phenomenon related to habit is called "mindless eating" (Wansink & Cashman, 2006). The hypothesis is that eating is so regular and effortless that our brains are typically not consciously aware of either the nutritional value of our food choices, or how design features influence eating. While this research has not adopted an explicit habit model like ours, the evidence is consistent with the conjecture that when people are eating habitually, they are generally not actively processing a lot of information about what they are eating.

One idea about mindless eating is that we "eat with our eyes". That is, our sensory systems try to regulate how much we are eating using senses like vision (rather than direct readouts from the stomach). In one ingenious study, subjects in an experiment ate from bowls of soup that were slowly being refilled from a hidden tube in the bottom of the bowl, which the subjects couldn't see (Wansink, Painter, & North, 2005). As subjects ate the soup, they could see that the level of soup in the bowl was going down slowly, and formed the implicit impression that they had not eaten very much. These subjects ate 75% more (six oz. extra) than control subjects. But they did not recall having eaten more, and did not say they felt more full.

An implication of the mindless eating hypothesis is that eating can be affected by the size of a portion of food, the amount in a package, and even features of tableware, utensils and glasses. For example, people typically underestimate the amount of liquid in a wider, shorter glass compared to the amount in a taller, thinner glass. You can therefore pour more in a wider, shorter glass and they will drink more. People who use larger plates at a self-service buffet put more food on their plate and eat more. A thorough meta-analysis of nearly a hundred studies of these effects concluded (Bucher et al., 2016):

> We found evidence that people consistently ate more food or drank more non-alcoholic drinks when offered larger-sized portions, packages or items of tableware than when offered smaller-sized versions…If an effect of this size were sustained across the whole diet it would be equivalent to around a 12% to 16% change in average daily energy intake from food among UK adults (p 3).

Defining habit purely in terms of preference complementarity has certainly been useful for some specific purposes. In our view, however, there are three limits to this approach that our two-system model is intended to extend.

First, the preferences-only approach gives no guidance about what variables cause habitual choice to end and shift to deliberative preference-based optimization. Our approach emphasizes the general two-controller model of choice and substitutes persistence of *choice* (during habit) for persistence of consumption driven by utility. This shift also invites consideration of questions like, "given environmental stationarity and

[17] There is similar persistence in Indian immigrant preferences for foods from their birth regions (Atkin, 2013) and in European immigrant preferences for redistribution based on norms in their birth country (Luttmer & Singhal, 2011).

action costs, what is the ideal mixture of habit and preference-based choice?" This question does not make sense if habit is driven by preferences.

Second, if current consumption utility is increasing in past consumption, then reward signals associated with consumption should be larger if the same good is chosen repeatedly (assuming utility generates reward signals). In the habit approach, the subjective value of a good does not change based on previous consumption. We know of no such evidence that persistent consumption increases reward signals, despite many, many studies on the learning of reward, ranging from direct measures of neural firing in monkeys to human fMRI. This idea of increased reward (sometimes called "sensitization" in psychophysics) is just not very biologically plausible as a general principle.

Third, a combination of evidence and intuition suggest that the development of habit can be identified empirically by multiple behavioral and cognitive markers (see Table 1). This is a large empirical advantage of our approach. The adjacent-complementarity and state-dependence approaches do not say anything about these markers because they do not specify the algorithm or mechanism by which habits work.

Establishing habituation by insensitivity to devaluation (as in the Adams-Dickinson rat experiments) has been challenging in humans. Being able to identify habit with a variety of measures is one way to work around this challenge.

Table 1: Empirical markers of habitual and preference-based choice modes

	Choice Mode	
Empirical Marker	**Habit**	**Goal-directed**
Choice Persistence	Persistence	requires preference changes
Own-Price Elasticity	low short-run	high short-run
Cross-Price Elasticity	zero, can be wrongly-signed	>0 substitutes, <0 complements
Choice Speed	Fast	Slow
Attention	Low	High
Purchase memory	Inaccurate	Accurate
Explicit explanation for choice?	No	Yes

The first three empirical markers, relating to ***choice persistence***, ***own-*** and ***cross-price elasticities***, have already been discussed.

Animal and human studies also show that habitual choices tend to be made quickly (***fast response times***). This is a key property because response times are easy to measure. If habits aren't fast they aren't worthwhile.

In addition, we conjecture that ***less attention*** is used in habit mode. While attention has not been measured in most of the studies that show consumption persistence, indirect evidence indicates that people often do not shop around much. For example, in the De los Santos, Hortaçsu, & Wildenbeest (2012) study of internet book shopping, 90% of people look at only one site within a day. Even in a seven-day window, 76% look at only one site. Marketing studies beginning in the 1970s show single-retailer shopping and low information acquisition is common, even for cars and expensive appliances (Newman & Staelin, 1972).

We also expect that people will ***remember*** habitual choices inaccurately (since inattention limits memory creation). An example of this memory effect is checking mobile cell phones: In one study people remembered having checked their phones 37.20 times/day, but the actual measured rate was 84.70 times (Andrews, Ellis, Shaw, & Piwek, 2015). An anecdotal example of this habit amnesia comes from author Camerer's partner. She often orders online deliveries from Amazon. She was shocked when Amazon sent a congratulatory note about how many purchases she had made over several years—1500. Remember that in our simple model, the consumer does not need to keep track of the purchase history. She only needs to remember the most recent choice and its doubt stock.

Finally, in most of cognitive neuroscience habits are thought to be ***implicit, not consciously known*** (Seger & Spiering, 2011). We conjecture that if you asked someone *why* they made a particular habitual choice, they would find it hard to explain in depth. They might answer superficially that "I usually do it this way" and "it's been good in the past". In a sense, those answers—as ridiculously vague as they are-- are actually a good reflection of their cognition during habitual choice. "I usually do it this way" refers to the recall of previous choice. "It's been good in the past" is the simple way of saying "the doubt stock was low".

In contrast, a preference-based choice of, say, a home or a dinner at a new restaurant would probably refer to attributes of the choice, prices, the qualities of alternatives, and so on.

The last two empirical markers of habit– poor memory and explanatory depth – may not seem to be important economic variables. But memory and explanation are often inputs to other kinds of economic decision making. For example, many household surveys rely on memories of purchases. The Consumer Expenditure Survey (CES) uses both quarterly surveys and weekly "diary recordings" to measure large and small expenditures. The CES is economically important because it is an input to inflation estimates (CPI). While households are encouraged in their diaries to record everything they buy, it is conceivable that habitual purchases are underreported. Understanding more about the habit-memory link will help bound how common biases are, and help limit them.

Explanations of reasoning for choices are important too, for educational, organizational, legal, and political purposes (Derek Willis, 2015). In parent-child, teacher-apprentice, and manager-trainee relationships, if the more experienced person is making habitual choices and cannot explain why, their ability to foster human capital development by teaching junior learners is limited. In court proceedings, explanations of why defendants took certain actions can have important legal consequences. Thus, while psychological markers of habit like decision speed, memory, and explanatory quality are certainly not the typical variables of economic interest in studying decision making, we hope to measure them and explore how they could be useful.

We conjecture that there are two other empirical indicators of habit (though we have not derived these formally): Search costs, and habit interruptions.

Search and switching costs: In habitual choice, by our definition, consumers are not searching at all among a large set of choices which may be varying in price and quality.[18] As a result, during habitual search the foregone value of search will be high. Any empirical analysis which infers the costs of search from actual purchase patterns will therefore infer that search costs must be high (to reconcile the low amount of search with optimization).

Many studies have tested models of optimal search using a combination of prices, choices, and search data. In these models there is a hidden "search cost" and consumers are assumed to search optimally. A habitized consumer will not search at all; the model will therefore identify habit in the form of an inferred search cost which is high.

For example, De los Santos, Hortaçsu, & Wildenbeest (2012) estimate the cost of searching one extra online bookstore for a bestseller as \$4.14, assuming shoppers must search to learn prices (p. 2978). Hong & Shum (2006) estimate that half of subjects don't bother to search online for expensive textbooks; they buy at the first price. The estimated search costs for those who do search are about \$1.30-\$19 for the first additional search. Moraga-González, Sándor, & Wildenbeest (2013) estimate around \$8 for computer chips. If an extra search for a particular book is quick, this implies a high marginal search cost per hour. Using data on exact shopping cart locations in a store, (Seiler & Pinna, 2017) estimate a return from search of \$2.10/minute (=\$126/hour).[19]

De los Santos, Hortaçsu, & Wildenbeest (2012) also estimate rather low own-price elasticities for specific bestselling books at Amazon (from –.11 to -.65), while controlling for consumer knowledge of shifting price distributions. The Amazon elasticities are lower than other bookstores, which is consistent with habit if consumers use Amazon more regularly and form a habit.

It is also typical in these empirical search papers to find bimodality: A large fraction of consumers don't search beyond the first price, while others search more intensively. This is exactly what one would expect if some consumers are in habit mode and others choosing according to preferences (or model-directed in neuroscience terms). Of course, it is also likely that there are individual and lifecycle differences in search intensity.

Several other economic papers study "inertia" in consumer choice. These papers do not fit models of optimal search; instead, they usually compare the costs and value of current purchases with opportunity costs from switching. It is possible that inertia is due to habit much as we model it, though these studies do not estimate habit explicitly. Luco (2017) gets empirical leverage from comparing new consumers with those who have been purchasing for a while, in Chilean pension plan enrollment. He estimates an inertia cost of \$37.50/month. Other estimated inertia costs seem to be high: \$280 (online grocery

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[18] Turning to search raises the question of how our approach is related to "satisficing" (see the clear experimental evidence from (Caplin, Dean, & Martin, 2011). Satisficing is truncation of a search process after reaching a utility goal. Habit is shifting from a preference-based decision process when repeated choice rewards are stable enough. There may be some interesting formal familial-relation between the two concepts that would be useful to establish.

[19] Intriguingly, they also find heterogeneity in imputed search costs for different locations in the store. This implies that product location is an important aspect to consider in habit formation. Consistent with some animal learning studies, even human shopping habits might be very specifically constrained in time and space, or to particular motor actions.

delivery, Goettler & Clay (2011), $2500 (health insurance, Handel (2013) and $4000 (Medicare, Nosal (2012). Hortaçsu, Madanizadeh, & Puller (2015) estimate it would take Texas households only 15 minutes to save $100/year on electricity by switching. They also find that having an increase in last month's electricity bill increases search for a new supplier, which is quite consistent with the idea that absolute prediction error jars people out of habit.

Habit interruption: Another implication of our habit concept is that exogenous interruption of habits, typically through product unavailability, can trigger a preference-based search. If the former habit good is unavailable for a while, its doubt stock rises over time. After a while the consumer is unlikely to resume the habit when the product becomes available again. We have not done formal analysis of when returning to old habits does and does not happen, but that is a natural and interesting extension of our modeling.

An intriguing analysis of the result of interruption is based on a two-day strike by workers in the London subway (Tube) system in February 2014 (Larcom, Rauch, & Willems, 2017). This is an ideal natural experiment because the strike only closed part of the Tube routes; commuters affected by strikes could then be compared with those who were not affected. Oyster swipe cards also make it easy to record when and where commuters got on and off trains. Furthermore, the London Tube maps are not drawn to scale (they were created to look like compact circuit diagrams). As a result, a commuter who must get out at a new Tube stop and walk the rest of the way to work cannot judge precisely from the map how far they need to walk. They must learn, to some extent, from trial-and-error which will generate RPEs in learning.

During the strike, about 63% of commuters could not take their regular route. Consider habitual commuters, who had taken the same route for all 10 weekdays before the strike. After the strike, 5.4% more of them switched to a new route (compared to commuters who hadn't been affected by the strike and did not switch).[20] The switch saved an average of 40 seconds of time. Extrapolated over several years of commuting, (Larcom et al., 2017) estimated that the subjective search cost required to rationalize the fact that these commuters had stuck with a regular commute, but immediately switched because of the strike, was **£**380 (=$636 in 2014).

The strike study raises an interesting question about how technology, regulation, and governmental action could enhance welfare with habitized consumers. The authors of the Tube study actually suggest that because commuters appear to search too little, the interruption due to strike was welfare-enhancing for commuters as a whole. This is a dramatic claim because it implies that in general, government actions which specifically make products or services unavailable for a short time, forcing search, can help people make better decisions.

Of course, there might be more efficient regulatory ways to improve consumer choice in the face of habit than occasional service-worker strikes. Regulation could force or subsidize exploration of new products, although competition in private markets may do so adequately without government intervention. Technological solutions which enable consumers to search quickly and in a personalized way could also interrupt habituated choice and inform habituated consumers about better products.

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[20] Note that creation of a new habit after an interruption is evidence against the common economic assumption that habits are a reflection of an increase in utility from making the same choice persistently.

Indeed, what happens in a market when firms know that consumers are habitual is an interesting question. Because habitual choice is price-inelastic, by definition, profit-maximizing firms have an incentive to search out habitual consumers or to help establish new habits. Some of this supply-side behavior will be consistent with imposing switching costs or making it easy to repeat-purchase (e.g. online auto-renewal). Another consequence of habit is that new and improved products may have a hard time breaking into a market dominated by habitual consumers. And finally, as in other areas of policy design, it will surely be useful to have a better understanding of the machinery which policies strive to influence— namely, the consumer or citizen brain-- to figure out how firms and governments can improve welfare of habit-prone consumers, without removing the mental benefits of efficient habit formation.

Conclusion

We have described a simple model of habit inspired by evidence from neuroscience and animal learningThe goal of models such as these is to have a sensible functional interpretation (what are habits *for*?), a tractable algorithmic specification which can be used to fit data and potentially prove theorems, and an underlying mechanistic implemention. In the model, habits are executed by recalling the previous choice (made in a particular environment or state) and a single number—the historical reward unreliability or doubt stock—and repeating the habitual choice of doubt is low. If doubt is too high, the decision maker reverts to a fuller goal-directed comparison of choices which is more effortful.

The model is used to make predictions about something extremely basic in economics—elasticity responses of demands to price and quality changes. The key insight is that a central neuropsychological definition of habit is insensitivity to devaluation of rewards from an action, which is the same as zero elasticity in conventional economic models. We can show that elasticities will be zero for small price changes, cross-price elasticities can have different signs, and own-price elasticity can be positive (violating the law of demand).

Furthermore, we predict that during habitual choice, people exert less mental effort, misremember their purchase history, and may have an impaired ability to explicitly (consciously) explain the basis for their choice. (These variables are not actually choices made in the simple model, they are simply empirical conjectures, though they could in principle be derived from a richer model.)

All of these hypotheses await empirical testing.

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